ARE THERE EFFECTS OF SELF-EFFICACY, INTEREST, AND OUTCOME EXPECTANCY IN STEM HIGH SCHOOLS?

Audrea L. Baker

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ARE THERE EFFECTS OF SELF-EFFICACY, INTEREST, AND OUTCOME EXPECTANCY IN STEM HIGH SCHOOLS?

by

Audrea Baker

A Dissertation
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Abstract

Low enrollment in STEM-related degree programs at the college level has been a national concern in the United States. Most American college students preferred to choose to major other than STEM majors. The purpose of this study was to examine if high school students’ extensive STEM experiences in high school would influence their STEM major decisions. The theoretical framework for this study was Lent’s Social cognitive career theory supported by some concepts from Bronfenbrenner’s ecological systems theory and Bandura’s social cognitive theory. This study used data from the High School Longitudinal Study of 2009 (HSLS:09), including self-efficacy, interest in math and science, math utility and science utility which served as outcome expectancy. The overarching research question is: Are there any effects of self-efficacy, interest, and outcome expectancy in STEM high schools? Specifically, did self-efficacy and interest predict outcome expectancy? How variances differ between self-efficacy, interest and utility for math and science in student’s who chose a STEM degree major and those who did not choose a STEM degree major. The results of two multiple regression analyses showed that self-efficacy and interest predicted math and science utility. The results of a multivariate analysis of variance (MANOVA) showed that the variances of self-efficacy, interest, and utility within math and science significantly differed between STEM degree majors and non-STEM degree majors. These relationships were especially strong in the areas of science interest and science utility within the student’s junior year of high school. The discussion chapter interpreted these results using the theoretical framework to highlight the importance of providing extensive STEM education in the high school years.

Keywords: STEM, High School Longitudinal Study 2009, ecological systems theory, social cognitive career theory, college degree major choice
# Table of Contents

<table>
<thead>
<tr>
<th>Chapter</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>List of Figures</td>
<td>iv</td>
</tr>
<tr>
<td>1. Introduction</td>
<td>1</td>
</tr>
<tr>
<td>Statement of Problem</td>
<td>1</td>
</tr>
<tr>
<td>Purpose of Study</td>
<td>2</td>
</tr>
<tr>
<td>Theoretical Perspective</td>
<td>3</td>
</tr>
<tr>
<td>Significance of Study</td>
<td>4</td>
</tr>
<tr>
<td>2. Literature Review</td>
<td>7</td>
</tr>
<tr>
<td>Bronfenbrenner</td>
<td>7</td>
</tr>
<tr>
<td>Bandura</td>
<td>9</td>
</tr>
<tr>
<td>Lent</td>
<td>11</td>
</tr>
<tr>
<td>STEM</td>
<td>16</td>
</tr>
<tr>
<td>High School Longitudinal Study of 2009</td>
<td>21</td>
</tr>
<tr>
<td>Status of Knowledge</td>
<td>25</td>
</tr>
<tr>
<td>3. Methodology</td>
<td>29</td>
</tr>
<tr>
<td>Framework</td>
<td>29</td>
</tr>
<tr>
<td>Sample</td>
<td>31</td>
</tr>
<tr>
<td>Independent Variables</td>
<td>32</td>
</tr>
<tr>
<td>Dependent Variables</td>
<td>34</td>
</tr>
<tr>
<td>Analysis</td>
<td>35</td>
</tr>
<tr>
<td>4. Results</td>
<td>39</td>
</tr>
<tr>
<td>Math Outcome Expectancy Regression</td>
<td>40</td>
</tr>
<tr>
<td>Science Outcome Expectancy Regression</td>
<td>43</td>
</tr>
<tr>
<td>MANOVA</td>
<td>47</td>
</tr>
<tr>
<td>5. Discussion</td>
<td>53</td>
</tr>
<tr>
<td>Learning Environment</td>
<td>53</td>
</tr>
<tr>
<td>Social Factors for Self-Efficacy</td>
<td>55</td>
</tr>
<tr>
<td>Career Choice</td>
<td>56</td>
</tr>
<tr>
<td>STEM vs. Non-STEM</td>
<td>57</td>
</tr>
<tr>
<td>Study Limitations</td>
<td>58</td>
</tr>
<tr>
<td>Contributions</td>
<td>59</td>
</tr>
<tr>
<td>Future Research</td>
<td>60</td>
</tr>
<tr>
<td>References</td>
<td>61</td>
</tr>
<tr>
<td>Appendix A: Math Regression Figures</td>
<td>71</td>
</tr>
<tr>
<td>Appendix B: Science Regression Figures</td>
<td>73</td>
</tr>
<tr>
<td>Appendix C: IRB Approval Letter</td>
<td>75</td>
</tr>
</tbody>
</table>
**List of Figures**

<table>
<thead>
<tr>
<th>Figures</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Lent Social Cognitive Career Theory Model (Found in Chapter 2)</td>
<td>13</td>
</tr>
<tr>
<td>2. This Study’s Framework (Found in Chapter 3)</td>
<td>30</td>
</tr>
<tr>
<td>3. Normal Distribution of Independent Variables for Math Regression Assumption (Found in Chapter 4)</td>
<td>40</td>
</tr>
<tr>
<td>4. Normal Distribution of Math Utility for Math Regression Assumption (Found in Chapter 4)</td>
<td>41</td>
</tr>
<tr>
<td>5. Scatterplot of Math Utility for Math Regression Assumptions (Found in Chapter 4)</td>
<td>42</td>
</tr>
<tr>
<td>6. Normal Distribution for Independent Variables for Science Regression Assumptions (Found in Chapter 4)</td>
<td>44</td>
</tr>
<tr>
<td>7. Normal Distribution of Math Utility for Science Regression Assumption (Found in Chapter 4)</td>
<td>44</td>
</tr>
<tr>
<td>8. Scatterplot of Math Utility for Science Regression Assumptions (Found in Chapter 4)</td>
<td>45</td>
</tr>
<tr>
<td>9. This Study’s Updated Framework (Found in Chapter 5)</td>
<td>56</td>
</tr>
<tr>
<td>10. Normal Distribution for Regression Assumptions 2009 Math Self-Efficacy and Math Utility (Found in Appendix A)</td>
<td>70</td>
</tr>
<tr>
<td>11. Normal Distribution for Regression Assumptions 2011 Math Self-Efficacy and Math Utility (Found in Appendix A)</td>
<td>70</td>
</tr>
<tr>
<td>12. Normal Distribution for Regression Assumptions 2009 Math Interest and Math Utility (Found in Appendix A)</td>
<td>71</td>
</tr>
<tr>
<td>13. Normal Distribution for Regression Assumptions 2011 Math Interest and Math Utility (Found in Appendix A)</td>
<td>71</td>
</tr>
<tr>
<td>14. Normal Distribution for Regression Assumptions 2009 Science Self-Efficacy and Science Utility (Found in Appendix B)</td>
<td>72</td>
</tr>
<tr>
<td>15. Normal Distribution for Regression Assumptions 2011 Science Self-Efficacy and Science Utility (Found in Appendix B)</td>
<td>72</td>
</tr>
</tbody>
</table>
   Science Interest and Science Utility (Found in Appendix B)

17. Normal Distribution for Regression Assumptions 2011
   Science Interest and Science Utility (Found in Appendix B)
Chapter 1

Introduction

Science, technology, engineering, and mathematics (STEM) are considered the engine of our country (McEntee, 2020). Careers in the STEM fields support 67% of jobs, 33% of the economy, and $2.3 trillion of tax revenue in the United States (McEntee, 2020). Lehman (2013) posits that the global economy depends on technological development, advances, and competition.

The purpose of this quantitative study was to examine if there are effects of self-efficacy, interest, and outcome expectancy in stem high schools. This study used the High School Longitudinal Study of 2009 (HSLS:09) to examine the effect of student self-efficacy (i.e., one’s belief about their capabilities), interest in math and science as well as the outcome expectancy, which will be proxied by the variables of math utility and science utility (i.e., one’s expected future value in math and science). The study will refer to the variables of math and science utility as outcome expectancy, unless otherwise needed. The theoretical framework for this study was Lent’s Social cognitive career theory based on the conceptual foundations of Bronfenbrenner’s Ecological Systems Theory and Bandura’s social cognitive theory to aid in the understanding of how STEM career choice may be influenced by a school’s environment.

Statement of Problem

Holmes, Gore, Smith, and Lloyd (2017) found that declining enrollment in STEM related degree programs at the college level was due to students’ lack of interest in STEM fields. Holmes, et. al based their study on several key issues to identify factors that could lead to a lack of interest in STEM fields including gender, prior academic achievement, and socio-economic status (SES). The study found that females were less interested due to feelings of being less
capable than their male counterparts. Another key issue found was that increasing social benefits in instructional approaches could increase interest with not only women but all students in the area of math and science. Last, when observing SES in relation to STEM interest, Holmes, et. al (2017) found that the intersectionality of race, gender and prior achievement, clouded the direct connection of whether SES alone attributed to the factor of student’s interest in STEM.

Holmes and colleagues (2017) reviewed studies from 2012 to 2015 on occupational choice found that students interested in STEM fields were more likely to be high achieving males that had a parent in a STEM field or were of higher cultural capital, meaning a part of a class of individuals whose skills and education gave them an economic advantage. Salem (2018) found in a Pew Research Center study on the decline of STEM degree choices that 52% of students included in the study stated the academic curriculum was too hard, leaving the role of educators to improve not only academic achievement but also to create interest in STEM professions. The academic rigor required in math and science courses may lead to students’ lack of interest in these courses and the subsequent decline in enrollment for STEM majors in higher education (Holmes, Gore, Smith, & Lloyd, 2017).

**Purpose of the Study**

The purpose of this study was to examine how immersion in a STEM-focused high school environment increases math and science self-efficacy and interest, how those variables affect the outcome expectancy of math and science and attainment of a post-secondary STEM major using the High School Longitudinal Study 2009 (HSLS:09). The HSLS:09 is a longitudinal assessment of data from a cohort of students beginning in their freshman year of high school and following them into year two of their post-secondary institute. Evidence shows that "high schools that offer a math and science-focused program are expected to help produce
students who are not only interested in math and science but have a better chance of majoring in STEM, once in college" (Bottia, Stearns, Mickelson, & Moller, 2017, p. 87). The research question for this study was: Are there Effects of Self-Efficacy, Interest, and Outcome Expectancy in STEM High Schools?

**Theoretical Perspective**

Environmental background factors can affect learning experiences through career-relevant self-efficacy, a belief in one’s own ability to complete a task given a set of environmental cues (Lent, Hackett, & Brown, 2000). Using Lent’s theoretical perspective of social cognitive career theory (SCCT), this study examined one’s environment of learning experiences, self-efficacy, interest, and outcome expectancy in the choice of and success in STEM-focused curriculum.

Lent’s framework of SCCT explains how self-efficacy, interest, and outcome expectancy may predict a personal goal of career choice. Adding to Lent’s framework, Bronfenbrenner’s ecological systems theory, focuses on how the environment of the exosystem uses activities and engagement for student learning. Lent also draws on Bandura’s modeling and socialization to analyze how the teaching and action of others influence student’s belief within themselves. Collaboratively, these theories aid in examining how immersion in a STEM-focused environment correlated to career choice through self-efficacy, interest, and outcome expectancy in math and science.

This study used the concept of the exosystem in Bronfenbrenner’s ecological model and Bandura’s social cognitive theory as the theoretical foundations in examining the importance of the environment to STEM major selection. SCCT served as the conceptual framework for the relationships in this study. SCCT defines three major characteristics of career development: how
academic and career interests develop, how educational and career choices are made, and how academic and career success is obtained (Career Research, n.d.). Lent, Brown, and Hackett (1994) first introduced SCCT based on Albert Bandura’s social cognitive theory. Lent’s research proposed that the perception of self-efficacy and outcome expectancy “figure in the development of interest” (Lent, Brown, & Hackett, 1994, p. 89). A more in-depth review of Bronfenbrenner, Bandura, and Lent are given in chapter two.

**Significance of the Study**

It is important to examine if immersion in a STEM-focused high school leads to a STEM degree selection in a post-secondary environment due to the high demand of STEM careers in the private sector and a lack of students majoring in these fields. STEM career choice is in decline (Lehman, 2013), but seemingly not due to financial factors, as 65% of those who hold a bachelor’s degree in a STEM field earn more money than non-STEM employees with a master’s degree and 47% in the STEM field have a higher income than those with a doctorate degree (Bureau of National Affairs, 2013).

Lopez, et al, (1997) found that not only is math self-efficacy critical in math and science related interests, but it is also predictive of science and technical based careers. Because math self-efficacy drives interest and career choice, it is important to determine the biggest influence on one’s belief in their abilities. Lorsbach and Jinks (1999) found that self-efficacy influences students’ perceptions of the learning environment, and this can change moment to moment based on the teaching and learning going on at that time. In the same study, it was found that students’ self-efficacy is dependent upon “components of the classroom environment that are determined by how such things as goals, incentives, and expectations are created and maintained” (Lorsbach & Jinks, 1999, p. 161).
Tseng, Chang, and Chen (2013) observed that when learning support is lacking in a mathematics curriculum, students’ learning interest also decrease, which causes an increase of negative attitudes. Therefore, collecting data in a STEM saturated environment provided key evidence when determining if immersion increased math and science self-efficacy, interest, and outcome expectancy, which then aided in the selection of a STEM-related major in a post-secondary school.

The purpose of this study was to understand if high school’s that are STEM-focused, increase students’ math and science self-efficacy, interest, and outcome expectancy enough for students to major in a STEM field during college. This increase could help stop the decline of STEM careers and in turn support self-efficacy and interests among minority groups of students in a STEM environment.

Summary

Since STEM careers are a major industry sector in our economy, STEM education must be embraced often and early by students. Both Bronfenbrenner and Bandura agree that an individual’s environment and social construct, or an idea that has been created and accepted by the people in a society (Merriam Webster, 2021) are crucial to one’s success.

Immersion in a STEM-focused high school provides a basis of study for Bandura’s social cognitive theory to determine if modeling and socialization within ones’ environment gives students is a better chance to build self-efficacy, interest, and outcome expectancy. This environmental phenomenon prompted Lent to further investigate the specific traits that determine those future endeavors. Bandura (1997) believed that the educational environment should prepare students with the efficacy beliefs, and interests to educate themselves in a variety of pursuits throughout their lifetime.
Using the SCCT theoretical framework Lent found that self-efficacy, interest, and outcome expectancy could later determine a career choice (Lent, Brown, & Hackett, 1994). This theoretical framework lent itself to examine the research question: Are there Effects of Self-Efficacy, Interest, and Outcome Expectancy in STEM High Schools?

The literature review in Chapter 2 will further explain Bronfenbrenner’s ecological theory, Bandura’s social cognitive development theory, Lent’s framework on social cognitive career theory, as well as how each of these relate to the study of STEM and the data brought forth by the High School Longitudinal Study of 2009 (HSLS:09). The review of literature will give insight into why this study is important and how it differs from prior researchers who also used the HSLS:09 dataset.
Chapter 2

Literature Review

The literature review begins with a discussion of Bronfenbrenner's Ecological Theory, specifically how the exosystem is a basis for understanding the learning environment needed for those who want to pursue a STEM career choice. This will be followed with a review of Bandura's social cognitive theory related to modeling and socialization in a STEM-focused environment. Both theorists have posited that an individual's environment is a key factor in human development.

Bronfenbrenner’s (1974) and Bandura's (1997) research informed Lent’s study on the effects of the environment, not only in human development but also in future career choices. A discussion of Lent’s social cognitive career theory and how the connection of self-efficacy, interest, and outcome expectancy in a particular field of study should increase the likelihood of pursuing that career choice.

The last two sections include discussions on STEM and HSLS:09. These sections contain reviews of STEM and the current educational lack of supply to meet the demands in the private sector within STEM related occupations. The literature review concludes with a discussion on the relevance of the HSLS:09 to the study of the importance of immersion in a STEM environment to increase interest in STEM-related fields.

Bronfenbrenner

Bronfenbrenner (1978) developed a way to examine human development using an ecological system that consists of five tiers. These tiers begin with the most immediate setting (microsystem). It progresses through the connection of two or more active settings.
(mesosystem), then moves on to an outside setting that indirectly affects human development (exosystem).

The last two tiers explain how culture and beliefs (macrosystem) can alter the lower three systems, and how changes take place over time (chronosystem) in the other four systems. Because Lent, Brown, and Hackett (2000) use the third tier to explain SCCT and the environmental influences and barriers that one can face when choosing an occupation, I will first explain Bronfenbrenner’s third tier, the exosystem. I will then link it to Lent and his colleagues’ view that an individual’s surrounding “environmental layers” filter their perception of biases when choosing a career (Lent, Hackett, & Brown, 2000, p. 45). This study will focus on Bronfenbrenner’s third tier, the exosystem, because of the STEM focused learning environment found in the High School Longitudinal Study of 2009 (HSLS:09).

**Exosystem**

This system is defined as one or more settings that "do not involve the developing person as an active participant but could affect them" (Bronfenbrenner, 1979, p. 25). Bronfenbrenner (1986) later characterized this as “external” to the developing person. Two connections must be established before determining that the outside setting is involved in human development. “1. The researcher must connect the events in the external setting to the microsystem. 2. The researcher must then be able to link the microsystem to developmental changes within the person” (Bronfenbrenner, 1979, p. 237).

The exosystem focuses on activities with which children can not only engage, but also on the kinds of people with whom they engage (Bronfenbrenner, 1974). Bronfenbrenner calls this system part of an enduring or familiar environment, where those interacting with the child are not strangers, but people with whom they have a relationship such as neighborhood children or...
the school classroom (Bronfenbrenner, 1974). An interesting factor in the exosystem is that the people engaging with the child have their own separate micro and mesosystem. Therefore, the combination of relationships and behavior can influence one another, aiding in the creation of belonging and identity. How Bronfenbrenner’s exosystem relates to a STEM-focused environment can be found later in this chapter.

**Bandura**

Albert Bandura’s social cognitive theory (1986) discusses how one’s individual actions, choices, and goals are influenced by self-efficacy, environment, and behavior (Mueller, Hall, & Miro, 2015). In addition, Stewart, Henderson, Michaluk, Deshler, Fuller and Rambo-Hernandez (2020) found that a person’s self-efficacy influences performance decisions, and future self-efficacy beliefs. The same study also references how modeling can aid in developing self-efficacy (Stewart, et al., 2020). Mueller, Hall, and Miro go on to discuss how social factors, such as teachers and professionals, can increase self-efficacy and aid in career paths. “Within this triadic system of self-efficacy, environment and behavior, people become both ‘products and producers of their environment” (Mueller, Hall, & Miro, 2015, p. 143).

**Self-Efficacy**

Self-efficacy is defined as the confidence one has in their abilities to complete a task given a set of cues (Burga, Leblanc, & Rezania, 2020). Self-efficacy can affect “behavioral functioning between individuals at different levels and function in individuals at different levels over time” (Bandura & Locke, 2003, p. 87). Later interpretation of Bandura’s theory found that it is not so much the “experience itself, but rather the interpretation or appraisal of the experience that determines its influence on self-efficacy beliefs” (Vaval, Bowers, & Rangel, 2019, p. 3). Such as, learners appraise their self-efficacy from their actual performances, vicarious
experiences, and the persuasions they receive from others within their environment (Schunk & Pajares, 2002).

Bandura and Locke also found that self-efficacy during the formative years can either hinder or aid in students’ occupational options. Using a longitudinal study starting at the beginning of junior high, research found that social structures and perceived self-efficacy predicted “occupational pursuits” by the end of junior high (Bandura & Locke, 2003, p. 90). During those formative years, Lorsbach and Jinks (1999) found that to increase self-efficacy schools should generate opportunities for students to engage in more self-determined learning. The same study also found that students who hold higher self-efficacy beliefs contribute more to the learning environment. Which could in turn shape the perception of others by use of modeling and socialization.

**Modeling**

According to Bandura (1971), modeling is a learned behavior that is influenced by the observation of an activity rather than the act of itself. In this type of learning the observer views a behavior produced by a “similar model or outside source” and the behavior is learned by the positive or negative interaction of that behavior (Masia & Chase, 1997, p. 41). Bandura also noted that adolescents tend to form friendships with those who hold similar values (Lerner, 1976), which would further prove that modeling is more effective when using people “with whom one regularly associates” (Bandura, 1971, p. 6).

**Socialization**

Another piece in Bandura’s (1971) social cognitive theory for adolescents is the idea of “social cues,” (p. 11) a term used to show how friends influence the way others may behave. One-way educators have combatted the issue of friends influencing another’s decision is to place
them on the same pathway. Students who participate in learning communities are often “housed together, take academic classes together, and are provided with educational and cultural programs to enhance the academic curriculum and social integration” (Carrino & Gerace, 2016, p. 1). Carrino and Gerace (2016) found that STEM-based learning communities, aid in academic success and increase graduation rates for students in STEM fields. This type of learning highlights how “students learn with others, through others, and from others, as well as the importance of collective relationships and social networks to an individual’s outcomes” (Carrino & Gerace, 2016, p. 2). The same study found that a nurturing community environment facilitated positive self-concept and self-efficacy.

Bandura’s theory of building self-efficacy through modeling and socialization aided in the framework of Lent’s SCCT. Those proximal influences of family, friends, and educators are needed to provide meaningful opportunities to aid in long-term goals for STEM students. Bandura’s idea of modeling and socialization and how it can build self-efficacy in STEM related fields can be found later in this chapter.

**Lent**

Bronfenbrenner’s ecological theory in human development focused on the larger social structure, where society is vital for developing the potential of human nature (Lang, 2005). Bronfenbrenner (1979) discusses in chapter two of his book, *The Ecology of Human Development: Experiments by Nature and Design*, that theorists have studied personality traits, developmental stages, temperament, and predominant behavior. Yet very little has been studied on environmental factors aside from one’s housing address. Lent, Hackett, and Brown (2000) also agree that most of SCCT’s work has focused on cognitive-variables in "isolation of important environmental variables" (Lent, Hackett, & Brown, 2000, p. 36). Bronfenbrenner
makes a point for psychologists to understand that human development consists of more than poverty and the setting from which one lives, but also an array of interpersonal and intrapersonal relationships with whom surround the individual.

Bandura, a cognitive behavioral theorist, focused on research with an emphasis on the role that cognitions play in behavior change (Capuzzi & Gross, 2010). Bandura emphasized the importance of observing, modelling, and imitating the behaviors, attitudes, and emotional reactions of others (McLeod, 2016). While Bronfenbrenner focused his research on how the environment affects the whole child, Bandura has focused his research on the interaction among "personal factors, behaviors, and environmental conditions" (Schunk & Meece, 2006, p. 72).

Utilizing both developmental science and cognitive behavior, Lent was able to form a theoretical framework of how people, behavior and a person's environment determine their career choices (Lent, 2005), it is called the social cognitive career theory (SCCT).

The purpose of SCCT is to explain how academic career interests develop, how education and career choices are made, and what factors affect academic and career persistence (Lent, et al., 2013). This theory is not just about career choices, but also about student’s overall success in that field. Individuals and their experiences are regularly affected by “aspects of the objective and perceived larger environment” (Lent, Hackett, & Brown, 2000, p. 45).

Below, in Figure 1, is Lent’s SCCT model followed by the variable definitions. Based on one’s environment, Lent believed that a student’s success transitioned from self-efficacy to outcome expectancy because the “outcomes people expect are largely dependent on their judgments of what they can accomplish” (Dong & Fabian, 2016, p. 372). Although, discussed later, this study will concentrate on an earlier framework of Lent’s (1997) research that self-
efficacy is a predictor of science and math content related interest, which leads to outcome expectancy and achievement.

**Figure 1**

*Lent’s SCCT Model*

**Self-efficacy**

Self-efficacy is the most investigated area of these variables due to its high correlation of career choice (Fouad & Smith, 1996). SCCT theorists suggest that self-efficacy strongly mediates through interest, with interest being a strong predictor of career choice (Kurban & Cabrera, 2020).

One environmental influence on self-efficacy pertains to how successful one has been at their past accomplishments (Lent, 2005). The study of self-efficacy is highly correlated to "personal and previous success and achievements" (Byars-Wisnton & Rogers, 2019, p. 31). If you have mastered a basic skill in one area, then the chances are you feel more confident to master another skill in that area. Each success will build, as will the confidence in yourself to complete those tasks (Mills, 2009).

In an article that Bandura co-wrote with Caprara, Fida, Vecchione, Del Bove, Vecchio, and Barbaranelli (2008), he specifically examines student's environment in a school setting to their perceived self-efficacy. This study found that learning activities, teacher's belief in student success, and a collective school-wide view of academic progress, aided in student self-efficacy
Outcome expectancy

Outcome expectancy is defined as the physical, emotional, or financial rewards that are associated with completing a task, and which are future-focused (Burga, Leblanc, & Rezania, 2020). Lent argued that the “underlying cognitive mechanisms proceed from self-efficacy beliefs to outcome expectancy because the outcomes people expect are largely dependent on their judgments of what they can accomplish” (Dong & Fabian, 2016, p. 372).

Outcome expectancy refers to the anticipated consequences of one’s involvement in a specific process or personal goal (Lent, Wang, Morris, Ireland, & Penn, 2019). Lent (1994) proposes that even a person with high self-efficacy in a content area might avoid a career in that field if he or she “anticipates a negative outcome” which could include non-support or other adverse barriers (Lent, Brown, & Hackett, 1994, p. 41). SCCT suggests that how individuals view those barriers could either prevent or motivate them in their success (Lent, Hackett, & Brown, 2000).

Interest

Scheuermann, Tokar and Hall’s research states that self-efficacy beliefs, outcome expectancy, and interests all figure prominently in SCCT models. In a study representing African
American women who were majoring in engineering, research data showed that their “self-efficacy for completing an engineering degree predicted subsequent engineering interests and major choice goals” (Scheuermann, Tokar, & Hall, 2014, p. 274). Their study also goes on to state that student’s interests may be assessed through ratings of occupational preference and/or activity preferences.

**Personal goals**

The last variable explored using SCCT is personal goals. Personal goals are defined as the ability to pursue the career chosen usually shown by how much value and importance is given to the field (Burga, Leblanc, & Rezania, 2020). SCCT suggests that self-efficacy and outcome expectancy “work in concert with ability, in part by influencing the types of personal goals that people set for themselves” (Story & Lepore, 2014, p. 752).

Personal goals rely on both ability and motivation (Luse, Rursch, & Jacobson, 2014). When a person has a high self-efficacy in a content area, they in turn have a more positive outcome expectation in the same content area. This increased self-efficacy and outcome expectation leads to better goal achievement (Mau, Chen, & Lin, 2019). Research shows that the cycle of self-efficacy and outcome expectancy are positively correlated, and these correlations affect personal goals (Byars-Wisnton & Rogers, 2019). Story and Lepore (2014) show a great connection of self-efficacy to an individual’s outcome expectancy with SCCT’s performance model. This model explains the level of success that people attain in educational and occupational interests and the degree to which they persist through difficulties. Their suggestion is to “expand interests and nurture career aspirations in children and adolescents, facilitate career goal setting and implementation in adolescents and young adults” (Story & Lepore, 2014, p. 753).
Having goals and experiencing growth toward one’s goals leads to higher satisfaction and attaining self-efficacy and success within one’s personal goals requires the right environment (Rasdi & Ahrari, 2020). Lent’s social cognitive career theory argues that a person’s environment plays a major role in developing confidence in a person’s ability and later goals and career choice. According to Lent, Wang, Morris, Ireland, and Penn (2019), self-efficacy is seen as nurturing positive outcome expectancy. Together these variables help to shape goals to pursue their career of choice.

**STEM**

Since it was noted that science, technology, engineering, and mathematics are considered the engine of our country (McEntee, 2020) and “the future of the economy is in STEM” (Vilorio, 2014, p. 3), it is imperative to investigate not only what STEM is, but also how educators can maintain the supply and demand to support the future needs of the country.

**STEM Fields.** The following will list each letter of the acronym of STEM and its need for career choice. The Bureau of Labor and Statistics (2014) found that those who work in the Science field often experiment, observe, and research the natural world. These workers tend to find career choices in life science, physical science, and/or the social sciences such as researching society and relationships. Those who work in the Technology field are the connecting lens for all communication. Understanding “operating systems, artificial intelligence, and programming” (Vilorio, 2014, p. 5) not only increase our countries innovative design in software, but also maintains and problem solves existing creations.

While technology might be considered the inner workings of our world, Engineering is the designer shell that makes our life “better and cheaper” to live in (Vilorio, 2014). Without the endless array of cellphones, tablets, and apps, one today would find it “difficult to imagine our
daily lives” (Fayer, Lacey, & Watson, 2017, p. 1). Engineering fields consist of civil, mechanical, industrial, electrical, and materials engineers. The last acronym in the STEM field is Mathematics, the foundational block for technology, engineering, and science. Workers in this degree field seek out logical relationships to create new findings in the real world.

**Job Demand.** Due to the importance of science, technology, engineering, and mathematic fields, it is important to determine not only the growth that has occurred in the STEM job market, but also where the future is leading. According to the Bureau of Labor Statistics (2017), in 2015 there were reported 8.6 million STEM jobs in United States. Of those jobs, 45% were in the field of computers and 19% were in the engineering field. Although in the past, math and science careers did not produce high percentages of job demand, they have an overall projected growth of 28.2% during the decade spanning from 2014-2024 (Fayer, Lacey, & Watson, 2017).

Wages are another factor when considering an occupation in STEM. The Bureau of Labor and Statistics (BLS) research in 2014 stated that workers in these career fields earn more than double other professions (Vilorio, 2014). The BLS research three years later stated that “this industry also had one of the highest average wages, across all occupations” (Fayer, Lacey, & Watson, 2017, p. 24). Thus, making the benefits of entering a STEM career choice more favorable for new graduates.

**Educational Supply.** The continued demand for STEM jobs must be met with an adequate supply in educational preparation. According to the Bureau of Labor and Statistics (2020), the occupations of software developers, software quality assurance analysts and testers is projected to have the most openings each year. Sadly, STEM employers are raising concerns
about the “quality of the U.S. educational system and its ability to produce a large enough workforce to fill these positions” (Wang & Degol, 2013, p. 305).

The United States Department of Education (2017) has tried over the last decade to put measures into place to aid in the educational groundwork for STEM careers. These examples fall into the following categories: (1) increase students’ equitable access to STEM courses and experiences, including out-of-school programs, STEM-themed schools, and career pathways; (2) support educators’ knowledge and expertise in STEM disciplines through recruitment, preparation, support, and retention strategies; and (3) increase student access to materials and equipment needed to support inquiry-based pedagogy and active learning (Department of Education, 2017, p. 1).

Wang and Degol (2013) stated that STEM career choices are a combination of choices and achievements that originate in childhood and adolescence. Since this study uses data that originated during the time of high school, adolescent age students, it aids in the examination of student’s gaining more STEM choices based on their age and environment.

**Bronfenbrenner Related to STEM**

As stated earlier, the exosystem focuses on activities with which children can not only engage, but also on the kinds of people with whom they engage (Bronfenbrenner, 1974). Bronfenbrenner’s enduring environment can lend itself to the probability that if a child is surrounded by positive modeling and activities related to math and science, they will develop high self-efficacy, enhancing the content area of math and science. This leads to the idea that immersing yourself in the right environment will create self-efficacy and success in learning. This can be concluded, based on Bronfenbrenner’s definition of human development, stating “one becomes motivated and able to engage in activities that reveal properties of greater
complexity in form and content” (Bronfenbrenner, 1979, p. 27). Thus, the gains of more STEM-focused activities and content will in turn motivate and engage the individual to a knowledge of greater complexity and success.

**Bandura Related to STEM**

Huang, Ball, Cotton, and O'Neal's (2020) theorized that students’ modeling of their teacher’s computer usage, will “positively influence students’ technology self-efficacy and STEM attitudes in the context of a computing intervention” (Huang, Ball, Cotten, & O'Neal, 2020, p. 215). The results of their study indeed found that observing teachers provided students with "increased opportunities to develop STEM attitudes" (p. 218).

Socialization is especially helpful for those who need extra motivation and cohesiveness in areas of STEM. This has also been shown to help recruit, develop, and retaining students in STEM disciplines and it has been shown to "increase student academic success, graduation rates, and post-graduation participation in STEM fields" (Carrino & Gerace, 2016, p. 1). Likewise, for students already showing high levels of interest in math and science, family support is a significant predictor in future goals (Mueller, Hall, & Miro, 2015, p. 151).

**Lent Related to STEM**

The environment is used to further the study of SCCT in a high school that is centered on the content of math and science. This setting is important to further investigate if high school exposure to math and science courses increases one's content area self-efficacy and achievement to later major in a STEM field (Wang, 2012). Wang looks at the critical importance of the “pipeline” to STEM academics and support, instead of just students who have already chosen this major in a postsecondary school (Wang, 2012, p. 2). The pipeline refers to the environment that students need to transition into STEM majors and ultimately career choices within the field.
Wang’s research provides an insight into social interaction between peers, faculty, and advisors as a major influence over student outcome (Wang, 2012, p. 7)

Since college is used for "transitioning" and training people for the workforce, it is important to know what fields students are interested in, what fields are needed in a growing economy and then adequately train those students to achieve success in that field (Burga, Leblanc, & Rezania, 2020). This type of research is particularly important in science, technology, engineering, and math (STEM) since these are the fastest-growing jobs in the United States (Falco & Summers, 2017).

There are four key variables that are linked to SCCT: self-efficacy, outcome expectancy, interest, and personal goals (Lent, Hackett, & Brown, 2000). As stated earlier, Lent’s research evaluated those four variables as seen in Figure 1 (on page 14), that learning experience (i.e., environment) should influence self-efficacy and outcome expectancy, which in turn will aid in one’s interest and goal in that content area. He stated that most people made their career decisions based on not only their self-efficacy and outcome expectancy but also their interest (Lent, 2005).

Although Lent has primarily focused his attention on this model, I find it important to spotlight his earlier (1989) research. His findings at that time show that significant relationships were found between self-efficacy and corresponding interests (Brown, Lent, & Larkin, 1989). I believe that current studies using SCCT leave a gap in how math and science self-efficacy play a role in one’s content interest and then the subsequent value (i.e., outcome expectancy) in the path to STEM career intention. You will find further explanation of this study’s adaptation of SCCT, in Chapter 3.
Self-efficacy and interest are operationalized in this study using a survey from the student’s freshman and junior year in a STEM immersed high school. The outcome expectancy enlisted in this study was found in the student survey during their junior of high school. Last, the intended STEM major in a post-secondary setting used as the final goal for this study.

Interest in math and science along with self-efficacy in the same content area is used in conjunction with outcome expectancy to determine one’s career goal. Lent states that goals, specifically choice goals are the “intention to engage in a particular action” (Lent, Brown, & Hackett, 1994, p. 94). The result of an individual having continuous exposure and nurturing to STEM activities to build STEM self-efficacy in high school may be positively related to higher outcome expectancy and ultimately leading students to pursue a goal in a STEM-field college major. The HSLS:2009 was a source of data that allowed an examination of this relationship.

**High School Longitudinal Study of 2009**

**Use of HSLS:09.** The High School Longitudinal Study of 2009 is a nationally representative longitudinal study with a special emphasis on STEM that provides an “opportunity for researchers to explore issues and ideas in STEM education using large-scale data” (Vaval, Bowers, & Rangel, 2019, p. 1158). This study examined 21,000, 9th grade students in 940 high schools. These students were surveyed in the 9th grade during the year 2009, as a base year of data. They were surveyed again in 2011 when the students were in the 11th grade, and in 2016 when students were continuing through postsecondary education (NCES, 2016). This study used HSLS:09 data to examine the relationship between self-efficacy, interest, and outcome expectancy within math and science courses and how those variables differed in those who chose a STEM major versus those who chose a non-STEM major.
Gottfried and Bozick (2016) found that interventions focused on an integrated STEM curriculum in high school “improved student outcomes” (Gottfried & Bozick, 2016, p. 178). The same study also found that this type of environment benefited students at the college level. This type of research influenced the decision to look further into high school environments that focused on STEM inclusively, using the HSLS:09 dataset. Stewart, et.al (2020) states that relatively few studies have measured self-efficacy at multiple time points, making this study unique in examining not only the relationship among self-efficacy and interest with STEM majors in a post-secondary institution, but also if student’s self-efficacy and interest fluctuate during high school.

**HSLS:09 in Education.** Recent findings show that high schools offering math and science-based program have become the focus of several policy initiatives and research projects. These schools are expected to help “produce students who are not only interested in math and science but have a better chance of majoring in STEM, once in college” (Bottia, Stearns, Mickelson, & Moller, 2017, p. 87). A STEM immersed environment provides consistent support, encouragement, and communal experiences, and are more favorable for student engagement and persistence (Morton, 2020). The HSLS:09 data was taken from high schools from around the country that fit the model of a math and scienced-based environment. Therefore, making HSLS:09 a valuable tool to determine what aids in producing STEM majors in college.

Bottia, Stearns, Michelson, and Moller's (2017) research further states that attending high schools with STEM programs "fosters the development of a stronger STEM-related self-concept and increases students' chances of having peers that are more interested in STEM" (Bottia, Stearns, Mickelson, & Moller, 2017, p. 100). Thus, substantiating the idea that attending high
schools with STEM programs may also foster the development of a stronger STEM-related self-concept and increase students’ chances of having peers that are more interested in STEM.

The participants in this research were students who were educated in a saturated STEM environment. The High School Longitudinal Study of 2009 (HSLS:09) is a longitudinal study that focused on a cohort of students in a high school that implemented a STEM curriculum. Therefore, the curriculum, activities, and relationships gained within their four years of attending, according to Bronfenbrenner’s theory, should positively increase their development in the areas of science, technology, engineering, and mathematics.

To investigate the effects of Bronfenbrenner’s exosystem, this research evaluated the data that follows the HSLS:09 cohort through high school and into their second year of post-secondary education. The study examined the student’s self-efficacy and interest in the subjects of math and science, first in their freshman year, and then again in their junior year to determine if their immersion in a STEM-focused environment aided in math and science outcome expectancy and ultimately their chosen major of a STEM career field.

This study’s intention was to determine if a STEM immersed environment could not only predict a student’s outcome expectancy of math and science based off their self-efficacy and interest, but also if those who chose a STEM degree differed in their self-efficacy, interest and outcome expectancy in math and science. To use Bronfenbrenner's exosystem in a STEM-focused environment, this study sought to connect two things: the events in the external setting to the microsystem and to link the microsystem to developmental changes within the person (Bronfenbrenner, 1979).

A STEM-focused high school met the criteria for an external setting because the developing individual was an active participant within the high school but did not have any
control over the curriculum and activities provided. The STEM immersion in this external setting was directly connected to the individual’s microsystem by the definition given by Bronfenbrenner, “a pattern of activities, roles and interpersonal relations experienced by the developing person in a given setting with a particular physical and material characteristic” (Bronfenbrenner, 1979, p. 22). The individual was experiencing not only the STEM activities but also the relations of modeling and participation from other students and teachers.

The second and final criterion that had to be shown, was the link between the microsystem and developmental changes to the individual. This research investigated the immersion and experience in a STEM environment to establish evidence of increased self-efficacy and interest within the STEM field. Because the HSLS:09 study focuses on a STEM saturated environment that is connected to an external setting, this study utilized the variables of math self-efficacy, science self-efficacy, math interest, and science interest, to determine if self-efficacy and interest predicted outcome expectancy. It also examined if those who declared a STEM major differed within those variables to student’s who declared a non-STEM major. Those outcomes will determine if the exosystem of Bronfenbrenner's ecological system applies to a STEM-focused environment.

A STEM-focused high school has the benefit of creating an environment that is enriched with STEM activities, socialization with peer groups, and extensive modeling in the courses of math and science. By integrating STEM courses within one learning environment, schools can “enhance the sense of achievement in learning, to improve learning attitudes and to increase continuity in learning” (Tseng, Chang, & Chen, 2013, p. 91)

Carrino and Gerace (2016) found that students who worked in learning environments such as peer groups/communities that specialized in STEM were found to improve in four areas,
academic self-regulation, STEM professional/science identity, metacognition, and self-efficacy. Which indicates that immersion in a STEM-focused environment has the potential to create higher self-efficacy. These inclusive opportunities can also give students a chance to engage in activities which could influence subsequent activity choices and further STEM involvement in post-secondary major or career choice (Carrino & Gerace, 2016).

One prominent factor that has been found as contributing to secondary school students' reluctance to major in a STEM-focused educational path and later career choice is low self-efficacy beliefs regarding STEM subjects (Aalderen, Walma Van Der Molen, & Xenidou-Dervou, 2018). Vaval, Bowers and Rangel (2019) found that attending an inclusive STEM high school can improve STEM participation, interest, and academic achievement suggesting that students who attend selective STEM high schools are “more likely to complete a STEM major in college” (Vaval, Bowers, & Rangel, 2019, p. 1154).

A study conducted by Saw, Chang, and Chan’s (2018) using the HSLS:09 data found that 11.4% of first-time 9th graders planned on majoring in a STEM field, and of those only about 34.3% maintained their interest until late 11th grade. Although prior research was conducted on student’s planned major in STEM, it is important to notice the decline in interest over time. This decline aided in this study’s investigation into not only interest, but also self-efficacy over time regarding STEM degree majors.

Status of Knowledge

According to Mau, Chen, and Lin (2019, p. 2), most studies focus on university students, who have already chosen a major of study, although, it has been found that starting at a younger age in middle or high school can “benefit and help kids prepare for college”. The difference between this study and previous studies is the use of longitudinal data from the HSLS:09. This
data begins with students who are just beginning high school and follows them throughout their secondary educational experience. Like other studies that examine data from university students only, this study analyzes data from high school students throughout their university studies. The high schools used in HSLS:09 empower a STEM-focused curriculum with data that tracks students' trajectories from the beginning of high school into postsecondary education.

Using Lent’s SCCT framework, Kurban and Cabrera (2020) chose to use the HSLS:09 data due to its STEM relevant items and exposure to STEM related content. They built on prior research that high school serves as the most prominent time for a student’s interests to align with their career goals. This study elaborates on the idea that during a child’s adolescence their “mathematical abilities contribute to the development of their self-efficacy” (Kurban & Cabrera, 2020, p. 621).

Kurban and Cabrera’s (2020) study used STEM self-efficacy and interest as determining variables, but it also included socioeconomic status, and parental involvement. Since SCCT suggests that self-efficacy has a direct effect on achievement and strongly influences ultimate career selection (Lent, Hackett, & Brown, 2000), it is only suitable that self-efficacy, interest, and career intentions act as variables to determine career selection. Another difference within the Kurban (2020) research was the ‘intention to major in STEM’ outcome variable. This data collection was taken in 2013, as part of the follow-up of student grades from the end of high school. This information reflects what the student anticipated majoring in when enrolled in a post-secondary institution or vocational school. The data used in this study reflects the students actual major during their second year of a post-secondary institution. There is a valuable difference to be examined within the constructs of what a student thought they would major in versus what they declared after a two-year enrollment.
The HSLS:09 has been used in other methods of research and data collection for purposes of STEM jobs, grades, teaching experience and family support in areas of math and science. The purpose of this study was to specifically examine how math and science self-efficacy and interest, predict the outcome expectancy and how those who chose a STEM degree differ in those variables compared to those who chose a non-STEM degree. This study utilized specific aspects of Lent’s SCCT model to determine if a student’s environment in high school aids in their choice of major in a STEM-focused field.

Summary

Together, Bronfenbrenner and Bandura describe an environment that gives an individual active exposure to specific content, models that content and includes communities of others who are also active in that content area. Bronfenbrenner describes the exosystem as one or more settings that "do not involve the developing person as an active participant but could affect them" (Bronfenbrenner, 1979, p. 25). Bandura also tied academic success to an individual’s environment through modeling. He stated that modeling is a learned behavior that is influenced by the observation of an activity rather than the act of it (Bandura, 1971). Bandura also believed that students who participate in learning communities are often “housed together, take academic classes together, and are provided with educational and cultural programs to enhance the academic curriculum and social integration” (Carrino & Gerace, 2016, p. 1).

Lent brings the concept of environment full circle to determine the future outcome of an individual. Lent's SCCT framework finds that self-efficacy, interest, and outcome expectancy play a major role in one's career choice. This review also included the understanding of STEM’s demand of the current job market and supply of educational backgrounds that produce such workers. This is examined by determining if immersion in a STEM-focused high school
environment increases math and science self-efficacy, interest, and outcome expectancy to attain
the goal of a post-secondary STEM major using the High School Longitudinal Study 2009
(HSLS:09).

The methodology in Chapter 3 will review the sample population collected from the
HSLS:09 data and discuss each variable used. Chapter 3 will also explain not only the design of
this study but also the adaptation from Lent’s SCCT framework to support the analysis of this
research.
Chapter 3

Methodology

This chapter discusses the adaptations of Lent’s SCCT model to fit specifically with this study. It also discusses the specific population of students selected from the HSLS:09 longitudinal data gained from the year 2009 (i.e., the students freshman year of high school) until the year 2016 (i.e., the students’ time of claiming a major in college). The variables used in this study are identified and described. Finally, the chapter will discuss the statistical analyses used to examine math and science interest, self-efficacy, outcome expectancy, and a degree major related to a STEM field. This chapter will address the overall research question: Are there Effects of Self-Efficacy, Interest, and Outcome Expectancy in STEM High Schools? Two separate analyses were conducted to examine:

(1) Do self-efficacy and interest predict outcome expectancy in the content area of math and separately in science?

(2) Do the variances within STEM versus non-STEM majors differ in math self-efficacy, interest, and outcome expectancy as well as science?

Framework

Adapted from Lent’s SCCT framework, the model seen in Figure 2 shows this study’s investigation of how immersion in a STEM-focused high school is influenced by self-efficacy, interest, and outcome expectancy. When these variables are combined within a STEM-supportive environment, it should positively predict a STEM-related major in a post-secondary school.
Byars-Winston and Rogers (2019) found that self-efficacy was highly correlated to "personal and previous success and achievements" (p. 31). Lent, Hackett, and Brown (2000) also include examples of exposure, support, or discouragement to student’s self-efficacy. Therefore, this study identified self-efficacy in math and science as a relevant predictor for a STEM major.

Lopez and his colleagues (1997), together with Lent, found that math self-efficacy predicted science and math content related interest, and that student’s develop interests in activities at which they view themselves to be “efficacious and for which they anticipate positive outcomes” (p. 45). Following this finding, the current study added in math and science interest to further to predict students’ STEM major.

Scheuermann, Tokar and Hall (2014) state that self-efficacy beliefs, outcome expectancy, and interests all figure prominently in SCCT models. In a study on high school students' math-related interest and performance, Lopez and his colleagues (1997) proxied outcome expectancy with an assessment of students' perceptions on the “relevance of mathematics to their future life and work plans” (p. 47). Therefore, the current study identified math and science outcome expectancy, or the measure of value one holds for this content area as a relevant variable to predict students’ STEM major.
Last, from Lent’s original model in Figure 1 on page 13, to this study’s modified framework in Figure 2, ‘outcome expectancy’ and ‘degree choice has exchanged positions. This is due to the investigation of how self-efficacy and interest affect one’s STEM-degree choice, which further their value of math and science (i.e., outcome expectancy) within this study. Lent (2016) believed that a student’s success transitioned from self-efficacy to outcome expectancy because the “outcomes people expect are largely dependent on their judgments of what they can accomplish” (p. 372). This study chose to focus on Lent, Lopez and colleagues’ (1997), earlier model in which self-efficacy is a predictor of science and math content related interest, which leads to achievement. In this study, that achievement is determined by finding value in math and science for one’s future.

Sample

The High School Longitudinal Survey of 2009 (HSLS:09) focused on student interests and goals specifically related to STEM. This seven-year data set details academic behavior (e.g., attendance, study habits), attitudes and beliefs (e.g., self-efficacy), social and cultural experiences, exposure to STEM through school or home activities, and negative school and STEM experiences (NCES, 2012). The gender and race represented in this dataset showed, 45% were male and 55% were female. The student population was categorized into 8 races, of which 60% were white, 12.3% were Hispanic, 11% were Asian, 8% were more than one race, 7.7% were African American, 4% were American Indian/Alaskan Native and .3% was Native Hawaiian / Pacific Islander.

The HSLS:09 data set was cleaned of all responses that were notated as unresponsive, not applicable, and/or chose not to respond in the variables of: math and science self-efficacy, math
and science interest, math and science outcome expectancy, and post-secondary major in a STEM field. The sample total for this study was 5,919 students.

**Weighted Data**

Weighted data from HSLS:09 was used to better ensure the sample data represented the target population. Student-level, longitudinal analyses from the base year of 2009 and the first follow-up year of 2011 will use the weight value labeled as W2W1STU. This weight is most appropriate for addressing research questions associated with changes in student data from those time periods (NCES, 2011). These weights also account for “differential selection probabilities and differential patterns of response/nonresponse” (NCES, 2011, p. 6). The weight of these responses was compiled in the published data of HSLS:09 and are included in this study of responses for self-efficacy and interest from the student’s freshman and junior year results in high school.

**Independent Variables**

The variables used in this study are considered composite variables (i.e., constructed, derived, or created variables). They are usually generated with responses from two or more questionnaire items or from the recoding of a variable (NCES, 2012). The list of questions used for each composite variable can be found below in the variable descriptions.

**Variable Descriptions**

**Math Self-efficacy.** This variable was a scale of the participants math self-efficacy; higher values represent higher math self-efficacy. Variable was created through principal components factor analysis and standardized to a mean of 0 and standard deviation of one. The coefficient of reliability (alpha) for the scale is .65 or higher.
The math self-efficacy question that was taken during the student’s freshman year and again during their junior year and asked: How much do you agree or disagree with the following statements? Each answer listed below was ranked on a scale of 1 to 4 with one representing ‘strongly agree’ and four representing ‘strongly disagree.’ (NCES, 2009-2012, p. 35).

- “You see yourself as a math person?”
- “Others see you as a math person.”
- “Most people can learn to be good at math.”
- “You have to be born with the ability to be good at math?”

Science Self-efficacy. The data collected in the science category of self-efficacy was noted the same as math self-efficacy. The science self-efficacy questions were worded in the same way, interchanging the word ‘math’ for ‘science’. The answers were also ranked on a scale of 1 to 4 with one representing ‘strongly agree’ and four representing ‘strongly disagree’.

- “You see yourself as a science person?”
- “Others see you as a science person.”
- “Most people can learn to be good at science.”
- “You have to be born with the ability to be good at science?”

Math Interest. This variable was a scale of the participants interest in their base-year math course; higher values represent greater interest in their base-year math course. This variable was created through principal components factor analysis and standardized to a mean of 0 and standard deviation of one. The coefficient of reliability (alpha) for the scale is .65 or higher.

The interest question that was taken in the student’s freshman year and again in their junior year and asked the following questions. Again, each answer was ranked on a scale of 1 to
4 with one representing ‘strongly agree’ and four representing ‘strongly disagree’ (NCES, 2009-2012, pp. 29, 30):

- “You are enjoying this class very much?”
- “Do you think this class is a waste of your time?”
- “Do you think this class is boring?”

**Science Interest.** Again, the data collected in the science category of interest was noted the same as math interest. The science interest questions were worded in the same way, interchanging the word ‘math’ for ‘science’. The answers were also ranked on a scale of 1 to 4 with one representing ‘strongly agree’ and four representing ‘strongly disagree’.

- “You are enjoying this class very much?”
- “Do you think this class is a waste of your time?”
- “Do you think this class is boring?”

**Dependent Variables**

**Variable Descriptions**

**Math Utility.** This variable was a proxy for outcome expectancy and was a scale of the participants perception of the utility of mathematics; higher values represent perceptions of greater mathematics utility. Variable was created through principal components factor analysis and standardized to a mean of 0 and standard deviation of one. The coefficient of reliability (alpha) for the scale is .65 or higher.

The questions used to assess the math utility variable were taken during the student’s junior year. The following questions were asked. Again, each answer was ranked on a scale of 1 to 4 with one representing ‘strongly agree’ and four representing ‘strongly disagree’ (NCES, 2012, pp. 35):
• “Math is useful for everyday life.”
• “Math is useful for college.”
• “Math is useful for a future career.”

**Science Utility.** This variable was also a proxy for outcome expectancy, and was collected in the science category, as was math utility. The science utility questions were worded in the same way, interchanging the word ‘math’ for ‘science’. The answers were also ranked on a scale of 1 to 4 with one representing ‘strongly agree’ and four representing ‘strongly disagree’.

• “Science is useful for everyday life.”
• “Science is useful for college.”
• “Science is useful for a future career.”

**Reference Degree Major of STEM.** Last, a dichotomous variable representing a reference undergraduate degree/certificate of science, technology, engineering, or math (STEM). This variable was the “undergraduate degree or certificate that was being pursued in February 2016” (NCES, 2016, p. 48). There are two coded categories for this variable: 1) indicates a non-STEM chosen major and 2) indicates a STEM chosen major. HSLS:09 has defined a STEM major as one of the following: Life and Physical Science, Engineer, Social Science, Architecture, Health, split across two STEM or STEM-related fields, and STEM field unspecified (NCES, 2012).

**Analyses**

This study used two types of analysis. The first type consisted of two multiple regression models. One was for examining math self-efficacy, interest, in relation to math utility, an outcome expectancy; the other was for examining science self-efficacy, interest, in relation to science utility, an outcome expectancy. These analyses could suggest how STEM-focused high
school programs might account for possible relationships between students’ interests/self-efficacy in math and science and their value of these two subject matters. The second type of analysis was MANOVA which was to explicitly assess what role each of these variables (i.e., self-efficacy, interest, and outcome expectancy) play in a student’s choosing of a STEM-degree major, once the student has entered college.

**Multiple Regression**

This study used two multiple regression analyses, one that predicted the effects of math self-efficacy and interest on math outcome expectancy and the second predicted the effects of science self-efficacy and interest on science outcome expectancy. Each multiple regression was proceeded by an examination the four assumptions of normally distributed variables, linear relationships between independent and dependent variables, independent variables are not highly correlated, and that the variance of errors is the same across all levels of the independent variables (Osborn & Waters, 2002).

For the first multiple regression model, math interest for 2009 and 2011, and math self-efficacy for 2009 and 2011 were used as independent variables. The outcome expectancy variable for this analysis was the students’ math utility for 2011. For the second multiple regression model, science interest for 2009 and 2011, and science self-efficacy for 2009 and 2011 were the independent variables. The outcome expectancy variable for this analysis was the students’ science utility for 2011.

These specific variables were chosen to examine how a change in math and science interest and self-efficacy for students enrolled in STEM focused high schools relate to the students’ outcome expectancy of those content areas. The first set of self-efficacy and interest data were collected in 2009 during their freshman year of high school. The second set of self-
efficacy and interest data were collected in 2011 during their junior year of high school. The data collected for math and science outcome expectancy were also taken in 2011, during the students’ junior year of high school.

**MANOVA**

This study examined the variances between self-efficacy, interest, and outcome expectancy in math and science for those who chose a STEM degree versus those who chose a non-STEM degree in college, using a multivariate analysis of variance (MANOVA). The MANOVA examined the assumptions of (Lund & Lund, 2018):

- The two or more dependent variables are continuous.
- The independent variable consists of two or more categorical groups.
- The data has an adequate sample size.
- There are no univariate or multivariate outliers.
- There is multivariate normality.
- There is a linear relationship between each pair of dependent variables for each group of the independent variable.
- There is homogeneity of variance-covariance matrices.
- There is no multicollinearity or high correlation between the predictor variables.

The independent variable used in this MANOVA was a dichotomous variable identified as referenced degree major. The dependent variables for the MANOVA were: (1) math interest for 2009 and again for 2011, (2) science interest for 2009 and again for 2011, (3) math self-efficacy for 2009 and again for 2011, (4) science self-efficacy for 2009 and again for 2011 and (5) math utility and science utility for 2011. These ten variables were used to compare whether math and science self-efficacy, interest, and utility vary by STEM major vs. non-STEM major.
Summary

Using an adapted model from Lent’s SCCT theory, this study used HSLS:09 data to determine (1) if self-efficacy and interest could predict the outcome expectancy of math and science, and (2) if the variances of math and science self-efficacy, interest, and outcome expectancy differ between those who chose a STEM degree versus those who chose a non-STEM degree. This framework was constructed on the hypothesis that if a student is placed in a STEM focused high school, their math and science self-efficacy and interest will predict their math and science outcome expectancy. The results of this adapted framework of SCCT were determined by using two multiple regression analyses and a multivariate analysis of variance.
Chapter 4

Results

This chapter describes the analytical process of this study through multiple regression analyses to assess math and science utility as outcome expectancy and through MANOVA to assess seniors’ choosing of degree major in STEM in college. The following sections will also report the analytical results. First, for the regression analysis, tests were conducted to ensure that the basic assumptions for conducting regression analysis were not violated before proceeding to regress the dependent variable on the independent variables. Then tests were conducted to ensure all the assumptions for conducting MANOVA were met before proceeding to on the students’ college degree major in STEM as opposed to non-STEM.

A multiple regression in general is used to understand the functional relationships among several independent variables to see what might be causing the variation in the dependent variable (Urdan, 2010). In this study, two multiple regression analyses were necessary since there was a ‘math outcome expectancy’ variable and a separate ‘science outcome expectancy’ variable. These independent and dependent variables will be further explained later in this chapter.

A multivariate analysis of variance (MANOVA) was used to examine statistical differences on multiple continuous dependent variables, and a categorical independent variable. In this study, the MANOVA compared whether the math and science self-efficacy, interest, and outcome expectancy combinations differ by STEM vs non-STEM groups. Due to this study having ten separate independent variables and one dichotomous dependent variable, a MANOVA was used to assess the variance of each group. These variables are also explained
further later in this chapter. I will go next to examine the data distribution to examine whether they meet the basic assumptions for conducting a multiple regression analysis.

**Multiple Regression Math Outcome Expectancy**

**Assumptions**

*Normality of Residuals.* The acceptable range for skewness is between -1 and +1 and kurtosis is between -7 to +7 (Watson, 2018). Figure 3 tests the relationship between the dependent variable and the independent variables. The example in Figure 3 shows a spherical pattern of data points for math self-efficacy and math utility\(^1\) between the range of -2 and 2 on both the x and y axis. This indicates a constant across all predicted values of outcome and falls within the acceptable range of normality. Scatterplots for the remaining variables can be found in Appendix A. Figure 4 below inspects the overall variance of residuals for the math utility, which displays normal distribution between -2 and 2.

**Figure 3**

*Normal Distribution for Independent and Dependent Variables (Math Self-Efficacy and Math Utility)*

---

\(^1\) Outcome expectancy is proxied by the variables of math utility and science utility for the purpose of analysis
**Linearity.** Figure 3 above, shows an example of a linear relationship between each predictor variable and the outcome. The loess line is shown to run very close to the identity line of zero. Scatterplots indicating similar loess lines for the remaining variables can be found in Appendix A. Similarly, in Figure 5, the data is supported by homoscedasticity, meaning the variance of the dependent variable is the same for all the data (Glenn, n.d.).

Although each predictor variable indicates a linear relationship to the outcome variable, the overall regression for math utility is shown to have a ceiling effect, as seen in Figure 5. A ceiling effect can occur when scores within the data are close to the maximum they can be. Thus, there may be bunching of values close to the upper point. (Simkovic & Trauble, 2019). The loess line in Figure 5 shows a consistent relationship close to the identity line and then a dramatic decline once the peak has been met. This type of ceiling effects can happen when rating scales are skewed so that it’s too easy to reach a perfect or near perfect score (Glen, Ceiling effect, n.d.).
Variance. Last, a test was conducted to see if the math data had an issue of collinearity. Variance Inflation Factor (VIF) and Tolerance Statistic (TOL) were used to test the collinearity of the independent variables. Results indicated that multicollinearity was not a concern. Dart (2013) states that the VIF should be below 10, and the TOL should be greater than 0.1. Table 1 shows that the math regression data met the assumption.

Table 1

<table>
<thead>
<tr>
<th>Analysis of Variance of Math Efficacy and Math Interest</th>
<th>95% CI</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SE</td>
<td>LL</td>
</tr>
<tr>
<td><strong>Math</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-Efficacy 2009</td>
<td>0.014</td>
<td>0.003</td>
</tr>
<tr>
<td>Self-Efficacy 2011</td>
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</tr>
<tr>
<td>Interest 2009</td>
<td>0.014</td>
<td>0.050</td>
</tr>
<tr>
<td>Interest 2011</td>
<td>0.014</td>
<td>0.295</td>
</tr>
<tr>
<td><strong>Science</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-Efficacy 2009</td>
<td>0.001</td>
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</tr>
<tr>
<td>Self-Efficacy 2011</td>
<td>0.001</td>
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</tr>
<tr>
<td>Interest 2009</td>
<td>0.001</td>
<td>0.005</td>
</tr>
<tr>
<td>Interest 2011</td>
<td>0.001</td>
<td>0.022</td>
</tr>
</tbody>
</table>

** <.01
Results

A multiple linear regression was conducted to predict student’s math utility when attending a STEM-focused high school. Table 2 shows that both the math self-efficacy for the years 2009 ($\beta = .03, t = 2.20, p < .05$) and 2011 ($\beta = .174, t = 5.50, p < .001$), and math interest for the years 2009 ($\beta = .076, t = 12.23, p < .001$) and 2011 ($\beta = .334, t = 22.99, p < .001$) were significant predictors of math utility for the year 2011. The model accounted for approximately 25% of the variation in math utility for students 2011, junior year of high school ($R^2 = .255$)

Table 2

<table>
<thead>
<tr>
<th>Coefficients of Math Utility</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Math Self-Eff. 2009</td>
<td>0.176</td>
<td>0.014</td>
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<tr>
<td>Math Self-Eff. 2011</td>
<td>0.032</td>
<td>0.014</td>
</tr>
<tr>
<td>Math Interest 2009</td>
<td>0.078</td>
<td>0.014</td>
</tr>
<tr>
<td>Math Interest 2011</td>
<td>0.322</td>
<td>0.014</td>
</tr>
</tbody>
</table>

** <.01

Science Outcome Expectancy Regression

Assumptions

Normality of Residuals. The acceptable range for skewness is between -1 and +1 and kurtosis is between -7 to +7 (Watson, 2018). Figure 6 tested the relationship between the dependent variable and the independent variables. The example shown, shows a spherical pattern of data points for science self-efficacy and science utility$^2$ between the range of -2 and 2 on both the x and y axis. This indicates a constant across all predicted values of outcome and

---

$^2$ Outcome expectancy is proxied by the variables of math utility and science utility for the purpose of analysis
falls within the acceptable range of normality. Scatterplots for the remaining variables can be found in Appendix B. Figure 7 below inspects the overall variance of residuals for the science utility regression, which displays normal distribution between -2 and 2.

**Figure 6**

*Normal Distribution for Independent Variables*

![Partial Regression Plot](image)

**Figure 7**

*Normal Distribution for Science Utility*

![Histogram](image)

**Linearity.** Figure 6 above, also shows an example of a linear relationship between each predictor variable and the outcome. The loess line is shown to run very close to the identity line.
of zero. Scatterplots indicating similar loess lines for the remaining variables can be found in Appendix B. Similarly, the data is supported by homoscedasticity, meaning the variance of the dependent variable is the same for all the data (Glenn, n.d.).

Although each predictor variable indicates a linear relationship to the outcome variable, the overall regression for science utility is shown to have a ceiling effect, as seen in Figure 8. A ceiling effect can occur when scores within the data are close to the maximum they can be. Thus, there may be bunching of values close to the upper point. (Simkovic & Trauble, 2019). The loess line in Figure 8 shows a consistent relationship close to the identity line and then a dramatic decline once the peak has been met. This type of ceiling effects can happen when rating scales are skewed so that it’s too easy to reach a perfect or near perfect score (Glen, Ceiling effect, n.d.).

Figure 8

Scatterplot for Science Utility

Variance. Last, a test was conducted to see if the science data had an issue of collinearity. Variance Inflation Factor (VIF) and Tolerance Statistic (TOL) were used to test the collinearity of the independent variables. Results in Table 3 indicated that multicollinearity was
not a concern. Dart (2013) states that the VIF should be below 10, and the TOL should be greater than 0.1. Referring back to Table 1, shown again below, the science regression data met the assumption in this case.

Table 3

*Analysis of Variance in Science*

<table>
<thead>
<tr>
<th></th>
<th>95% CI</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SE</td>
<td>LL</td>
</tr>
<tr>
<td><strong>Math</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.034</td>
<td>0.011</td>
</tr>
<tr>
<td>Self-Efficacy 2009</td>
<td>0.014</td>
<td>0.003</td>
</tr>
<tr>
<td>Self-Efficacy 2011</td>
<td>0.014</td>
<td>0.147</td>
</tr>
<tr>
<td>Interest 2009</td>
<td>0.014</td>
<td>0.050</td>
</tr>
<tr>
<td>Interest 2011</td>
<td>0.014</td>
<td>0.295</td>
</tr>
<tr>
<td><strong>Science</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.005</td>
<td>0.008</td>
</tr>
<tr>
<td>Self-Efficacy 2009</td>
<td>0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>Self-Efficacy 2011</td>
<td>0.001</td>
<td>0.006</td>
</tr>
<tr>
<td>Interest 2009</td>
<td>0.001</td>
<td>0.005</td>
</tr>
<tr>
<td>Interest 2011</td>
<td>0.001</td>
<td>0.022</td>
</tr>
</tbody>
</table>

** <.01

**Results**

A multiple linear regression was conducted to predict student’s science utility when attending a STEM-focused high school. Table 4 shows both the science self-efficacy for the years 2009 (β = .081, t = 6.04, p < .001) and 2011 (β = .121, t = 7.45, p < .001), and science interest for the years 2009 (β = .099, t = 8.60, p < .001) and 2011 (β = .352, t = 25.08, p < .001) were significant predictors of science utility for the year 2011. Table 5 shows that the model accounted for approximately 25% of the variation in science utility for students 2011, junior year of high school (R² = .252).
Table 4

Coefficients of Science Utility

<table>
<thead>
<tr>
<th></th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B (Std. Error)</td>
<td>Beta (T) Sig</td>
</tr>
<tr>
<td>Science Self-Eff. 2009</td>
<td>0.008 (0.001)</td>
<td>0.121 (8.600) 0.000**</td>
</tr>
<tr>
<td>Science Self-Eff. 2011</td>
<td>0.006 (0.001)</td>
<td>0.081 (6.043) 0.000**</td>
</tr>
<tr>
<td>Science Interest 2009</td>
<td>0.007 (0.001)</td>
<td>0.099 (7.454) 0.000**</td>
</tr>
<tr>
<td>Science Interest 2011</td>
<td>0.024 (0.001)</td>
<td>0.352 (25.076) 0.000**</td>
</tr>
</tbody>
</table>

** <.01

MANOVA

Assumptions

The multiple regression analyses and the MANOVA required to meet three same assumptions of (1) normally distributed variables, (2) linear relationships between independent and dependent variables, and (3) collinearity. However, the MANOVA also require to meet four separate assumptions. These four assumptions all concerned the type of variables used within the analysis (1) variables are continuous, (2) independent variable is categorical, (3) data is adequate in sample size. Last was (4) the test of homogeneity to determine if the samples were considered equal.

Variable Type. The MANOVA required the use of one independent categorical variable and two or more dependent continuous variables measured on an interval scale. The following were the three main dependent variables listed in the methods chapter: self-efficacy, interest, and utility. These were measured for the subjects of math and science separately. For the MANOVA, there was one dichotomous independent variable: referenced degree choice as STEM vs. non-STEM. Collectively, the two independent groups had a total number of participants: STEM
degree major (n=4388) and non-STEM degree major (n=1531); in total, the final sample for the MANOVA was 5,919, which was deemed adequate.

**Homogeneity of Variance.** Last, the assumption of homogeneity within the math and science self-efficacy, interest, and utility variables were analyzed using the Levene’s Test. The results of this test showed that: math self-efficacy for 2009, $F(1, 5917) = 1.15, p = .28$; math interest for 2009, $F(1, 5917) = 4.003, p = .05$; math self-efficacy for 2011, $F(1, 5917) = 9.12, p < .01$; math interest for 2011, $F(1, 5917) = 1.86, p = .17$; science self-efficacy for 2009, $F(1, 5917) = 0.03, p = .86$; science interest for 2009, $F(1, 5917) = 3.47, p = .06$; science self-efficacy for 2011, $F(1, 5917) = 6.52, p < .01$; and science interest for 2011, $F(1, 5917) = 15.19, p < .01$; math utility for 2011 $F(1, 5917) = 29.27, p < .01$; and science utility for 2011 $F(1, 5917) = 9.13, p < .01$.

**Sample Size.** The Levene’s test showed that only half of the variables met the assumption. While math self-efficacy from 2011, science self-efficacy from 2011, science interest from 2011, math utility from 2011, and science utility from 2011 violated the assumption for homogeneity. According to Glen (2018), this violation can happen when sample sizes are unequal. In this study, the sample sizes for students with a STEM degree (n=1531) versus a non-STEM degree (n=4388) were unequal. This violation is a limitation and affects the quality of the outcome for this study.

Further research into this assumption violation showed that one should test the equality of covariance matrices using Box’s M test. In cases where the test is significant, which it was ($p=.000$), then there may be “severe distortion in the alpha levels of the tests” (Harmon, 2016, p. 4). Harmon stated that only in this case should Pillai’s trace criterion be used. Glen (2016) also verified that Pillai’s trace is the most powerful test, especially if the MANOVA assumption of
homogeneity of variance-covariance is violated. Since Levene’s test of homogeneity was violated and Box’s M test showed a significant value, a Pillai’s trace was conducted. The result of that test showed: Pillai’s Trace = .110, $F = 73.138$, $df = (10, 5908)$, $p < .000$, indicating the assumption was met and that homogeneity was not a concern.

Results

Table 4 above shows results of the Wilks Lambda test, this was used to determine whether there were differences between the means of identified groups of subjects on a combination of dependent variables (Crighton, 2000). The results of this test ($\Lambda = 0.89$) showed that 11% of the variance in math and science self-efficacy, interest, and utility did explain the declared college major of a student in 2016.

Table 5 below depicts the descriptive statistics and results of the MANOVA. There was statistically significant difference in the mean value of students who chose a STEM degree major versus those who did not on the main variables.
The MANOVA test examined the difference in the value of math and science self-efficacy, interest, and outcome expectancy between those who majored in a STEM degree in college and those who did not, in their college year of 2016. The following narrative refers to Table 5, in explaining the effect size ($\eta^2$) of the student’s freshman and junior year, along with each separate dependent variable. The following examines the effect size and influence in order from greatest to least, on how much student’s outcome expectancy, self-efficacy, year of high school, and interest affected their later STEM-degree choice in college.

**Construct of Outcome Expectancy.** Although the effect size is small, science outcome expectancy shows a 5.2% ($\eta^2 = .052$) increase in student degree major choice. Math outcome expectancy showed an even smaller effect size of 3.3% ($\eta^2 = .033$) increase in student degree
major choice. With a difference of 1.9%, science utility shows most likely to contribute to what
degree major a students will make in college.

**Construct of Self-Efficacy.** Self-efficacy appears to hold the second highest percentage
in explaining student’s choice in college degree. In 2009, student’s freshman year of high
school, math self-efficacy contributed to only 3.6% ($\eta^2 = .036$). Comparably science self-efficacy
contributed to 3.4% ($\eta^2 = .034$). In 2011, student’s junior year of high school, math self-efficacy
contributed to 4.6% ($\eta^2 = .046$) of the variance. Similarly, science self-efficacy was 4.1% ($\eta^2 =
.041$) Although, between the student’s freshman and junior year of high school, we see a 1%
increase in effect size for self-efficacy as a predictor of degree choice in college.

**Time (2011).** Examining the effect size for the student’s junior year self-efficacy, interest, and outcome expectancy on STEM vs. non-STEM degree holders, the analysis shows
that there was a slightly increased, but still there is a comparable effect size for each variable. Just as the freshman year (i.e., 2009) self-efficacy scores were found to account for STEM degree majors, student’s junior year (i.e., 2011) scores also held higher percentages on explaining degree choice. Math self-efficacy contributed to 4.6% ($\eta^2 = .046$) of the variance, whereas science self-efficacy was 4.1% ($\eta^2 = .041$). A slight deviation from the freshman year, interest in math increased to 3.3% ($\eta^2 = .033$), whereas science interest decreased to 1.7% ($\eta^2 =
.017$).

**Time (2009).** When examining the effect size for the student’s freshman year self-efficacy and interest on STEM vs. non-STEM degree majors, this analysis shows that math self-efficacy contributed to only 3.6% ($\eta^2 = .036$), while science self-efficacy contributed to a comparable 3.4% ($\eta^2 = .034$). Similarly, math interest contributed to 2.1% ($\eta^2 = .021$) and science interest, only 2.2% ($\eta^2 = .022$).
Construct of Interest. Last, the MANOVA results indicated that interest was the least determining factor in relating to student’s degree major in a STEM field with the highest effect size being 3.3% ($\eta^2 = .033$) for math in the student’s junior year. The lowest effect size when examining all the variables combined (i.e., self-efficacy, interest, and outcome expectancy) was science interest. The student’s junior year effect size for science interest was only 1.7% ($\eta^2 = .017$). This difference of 1.6% aids in understanding a substantial gap in interest through the content area of math and science, when predicting student’s choice in degree major in college.

Summary

The key question that this study sought to answer was: Are there Effects of Self-Efficacy, Interest, and Outcome Expectancy in STEM High Schools? The multiple regression analyses and the MANOVA analysis show that there is a significant effect size that indicate a positive connection between self-efficacy, interest, and utility for the content areas of math and science. Those effect sizes were higher in science self-efficacy and utility during a student’s junior year of high school, in relation to their degree choice.

Chapter 5 provides further discussion on how these results fit with existing literature with regards to the theories of Bronfenbrenner and Bandura, and how these findings fit specifically with the adapted version of Lent’s SCCT theoretical framework.
Chapter 5

Discussion

This discussion chapter interprets the statistical findings of this study while considering the literature. This study evaluates the learning environment of Bronfenbrenner's exosystem, as found in the atmosphere of a STEM-focused high school. This chapter also includes a discussion of how that environment lends itself to Bandura's ideas concerning the importance of socialization and modeling to aid in STEM learning (McLeod, 2016). This chapter also examines Lent's theoretical framework of how people, behavior and a person's environment determine their career choices (Lent, 2005). Lastly, this chapter discusses limitations of the study and where future researchers should focus.

Learning Environment

This study’s multiple regressions analyses found statistically significant outcomes that science and math self-efficacy and interest could benefit student's outcome expectancy in those content areas. Therefore, attending a STEM-focused school could allow students to find worth for math and science in the future. The findings of this study suggest how a STEM-focused high may affect students’ future choices of STEM degrees through the model of Bronfenbrenner’s exosystem. An example of this affect can be seen in the increase of student’s self-efficacy, interest and outcome expectancy percentages throughout their high school year and subsequent relation to STEM degree choice.

Two connections had to be established before determining if a STEM-focused learning environment could fit the model of Bronfenbrenner's (1979) exosystem: first, the events in the external setting had to connect to the microsystem, and second, the microsystem had to connect to the developmental changes within the individual. The first question, the event in the external
setting must connect to the microsystem, was answered using the definition of Bronfenbrenner's (1979) exosystem. Being immersed in a STEM high school was connected to the individual's microsystem (i.e., immediate environment in which the child develops) using science and math activities as well as relationships with teachers and other students. These activities and relationships gave the individual, experiences which aided in human development.

Martin-Hansen (2018) examined how relationships between teachers and other students connect to a child’s microsystem. She explored how human development, specifically in educational environments (i.e., STEM-focused high school) are based on an individual’s STEM identity. Her research suggests that student-to-student and instructor-to-student relationships are vital. She also suggests that the STEM environment requires a mentorship role or an influential person who can be of support when cognitive and emotional burdens arise. This can build a student’s self-efficacy, interest, and value of STEM.

The second criterion, the microsystem had to connect to the developmental changes within the individual, needed to be shown to apply itself to Bronfenbrenner's exosystem. The purpose of this criterion was to link the microsystem to the developmental changes of an individual. Developmental changes (i.e., human development) were defined by the United Nations Developmental Program as "enlarging freedoms so that all human beings can pursue choices that they value" (Jahan, 2016, p. 15). This can be shown using the results of the Wilks Lambda test ($\Lambda = 0.89$). As it showed that 11% of the variance in math and science self-efficacy, interest, and utility did explain the declared college major of a student while in college test. Thus, revealing that developmental changes were developed when attending a STEM-focused high school.
The study’s STEM-focused environment, as provided by the HSL:09 data, aided in 25% of students majoring in a STEM degree. This can be found by factoring in the total number of students who participated in this study (n= 5,919) with those who declared a degree major in a STEM field (n = 1,531). This, in conjunction with the statistically significant findings of both the MANOVA and the multiple regression, indicate that the math and science-focused learning environment can be connected to the developmental change of an individual. This STEM learning environment (HSL:09) gave student's potential to further their studies through college and gain career opportunities in math and science.

Social Factors for Self-Efficacy

While examining student's variance when choosing a STEM degree or a non-STEM degree, this study found an increase in math self-efficacy from 2009 to 2011. A similar increase was also found in science self-efficacy from 2009 to 2011. Thus, showing Bandura's belief that goals (i.e., career choice) can be influenced in part by self-efficacy, as indicated in this study.

Albert Bandura's social cognitive theory (1986) discusses how one's actions, choices, and goals are influenced by self-efficacy, environment, and behavior. Carrino and Gerace (2016) also found that a nurturing community environment facilitated positive self-concept and self-efficacy. Mueller, Hall, and Miro (2015) look further into Bandura's theory and apply how social factors, such as teachers and professionals, can not only increase self-efficacy but also aid in career paths.

Career Choice

Although this study could not answer the question of how self-efficacy, interest, and outcome expectancy led to career choice, it did give insight into how those variables were related to goals as referred to in STEM degree choices. Lent and his colleagues (1994) stated that goals,
specifically choice goals are the "intention to engage in a particular action" (p. 94). Lent (2005) also stated that most people made their career decisions based not only on their self-efficacy and outcome expectancy, but also on their interests. The result of individuals having continuous exposure to STEM activities to build STEM self-efficacy in high school, are shown to be positively related to higher outcome expectancy. This progressive continuum will ultimately lead students to pursue a goal in a STEM-field college major.

The following narrative offers insight showing how math and science self-efficacy and interest play a part in the potential outcome expectancy within the math and science content areas. These relationships could help a student's future degree major and lead to a selection of career choices.

**Outcome Expectancy**

Lent's (1997) research suggested that self-efficacy is a predictor of science and math content-related interest, which leads to outcome expectancy and achievement. Therefore, it is important to examine how math and science self-efficacy and interest predicted the outcome expectancy of math and science.

The multiple regression results of this study revealed that Lent's framework of math and science self-efficacy and interest did well in predicting math and science outcome expectancy. This study indicated that 24.5% of the variance for math utility was due to math self-efficacy and interest. Science utility revealed a similar finding that 24% of the variance was due to student’s self-efficacy and interest. Since roughly a quarter of the sample was influenced by these variables, they suggest that Lent's theory of self-efficacy and interest predicting math and science utility is highly possible.
In the math and science MANOVA analyses, the most significant predictors were found within the student's junior year of high school. Math and science outcome expectancy were shown to be predicted by the student’s junior year (i.e., 2011) self-efficacy and interest data. Due to these findings, one could omit the 2009 math and science self-efficacy and interest data within the student's freshman year, as it does not show to influence outcome expectancy in those content areas.

Since the freshman year data from 2009 did not hold any major significance in neither math and science outcome expectancy nor the STEM vs non-STEM degree choice, the previously adapted framework has to be revised to reflect these findings (see Figure 9). The 2009 math and science data has been removed to better reflect the findings of this study.

Figure 9
This Study’s Framework

STEM vs Non-STEM Degree Choice 2016

<table>
<thead>
<tr>
<th>Self-Efficacy / Interest</th>
<th>→</th>
<th>Outcome Expectancy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Math</td>
<td></td>
<td>Math Utility 2011</td>
</tr>
<tr>
<td>11th Grade: 2011</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Science</td>
<td></td>
<td>Science Utility 2011</td>
</tr>
<tr>
<td>11th Grade: 2011</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**STEM vs. Non-STEM**

A previous study by Lent, Brown, and Hackett (1994) showed that Self-efficacy, interest, and outcome expectancy could later determine a career choice. The MANOVA results for this study examined students who chose a STEM degree major versus those who chose a non-STEM degree major and found supporting evidence that self-efficacy, interest, and outcome expectancy are important factors in a degree major choice. The between-subject analysis for STEM versus
non-STEM majors showed that the student's 2011 science interest and 2011 science outcome expectancy were the biggest predictors.

It is worth noting that in this study that science ($\eta^2 = .052$), not math ($\eta^2 = .033$) appeared to be the content area with the highest effect size, which confirmed the research of Estrada, Woodcock, Hernandez, and Schultz (2011) that anticipated mathematics self-efficacy as playing a critical role in developing STEM interest but found students who had higher self-efficacy toward science were more likely to consider a STEM career. Similarly, a study conducted by Kwon, Vela, Williams, and Barroso (2019) found that science self-efficacy, not math, showed a stronger relationship with students pursuing STEM careers.

**Study Limitations**

There were four major limitations in this study. The first constraint was the age of the data. Although the HSLS:09 continued through 2020, it began in 2009. The data specifically collected in 2009, 2011, and 2016. Education can change fast, with innovative ideas and research. Thus, making the data from over a decade ago, a limitation.

The second constraint continues with the data gained from the 2009. The survey data from the student’s freshman year of high school did not show significant differences in predicting math and science outcome expectancy or college degree major. This problem could lead to questioning if time disparity were a reason for the lack of significance.

The third limitation concerns the assumption of linearity within the regression analyses. Both math and science were found to have a ceiling affect. This problem can happen when rating scales are skewed so that it’s too easy to reach a perfect or near perfect score (Glen, Ceiling effect, n.d.). Future research would need to provide a better Likert scale for gathering data on self-efficacy, interest, and outcome expectancy.
The last limitation was the outcome expectancy variable that was proxied by math and science utility. Although Lent proxied outcome expectancy with an assessment of students' perceptions on the "relevance of mathematics to their future life and work plans" (Lopez, Lent, Steven, & Gore, 1997, p. 47), this was only found once in his research. Although this did not seem to have any noticeable implications on this study, the variable could be further examined in representing Lent's idea of outcome expectancy.

Conclusion

This study sought to determine: (1) if a STEM-focused high school, fit the model of Bronfenbrenner's exosystem. (2) If Bandura's social cognitive theory, specifically socialization and modeling, affected degree choice. (3) If Lent's social cognitive career theory was suggested by not only researching self-efficacy, interest, and outcome expectancy but also how those affected STEM-degree choice.

Contributions

This study found that a STEM-focused high school did justify as a setting for Bronfenbrenner's exosystem. This study also observed significant findings of increased math and science self-efficacy and interest, which was an indicator of positive modeling and socialization within an environment. This study discovered that the student's junior year of high school was the leading predictor in math and science self-efficacy and interest when determining a student's outcome expectancy (i.e., value).

Last, this study found that examining older data, as well as variations of variables concerning outcome expectancy, could be a limitation. Future research could be completed using further survey questions on the existing HSLS:09 data. Researchers could also use updated data,
providing a more current analysis to compare schools that are STEM-focused versus a general, public school.

**Future Research**

This study leaves several pathways for further research. First, one should examine what percentage of students major in a STEM degree while attending a regular public-school program for comparison. The difference in that outcome would further support the foundation of high schools that primarily focus on STEM content. The revelation that 25% of students ended up majoring in a STEM degree field, was very significant. This could be even more valuable, if the number of students from non-STEM-focused schools was significantly lower.

Second, one should examine more recent data that utilizes self-efficacy, interest, and outcome expectancy. A more current snapshot could gain insight into STEM-focused schools and their prediction of STEM degree choice. Current data could also provide information on how new and innovative coursework increase growth in self-efficacy, interest, and value for math and science.

Last, using this study one could further explore why science, not math, self-efficacy and interest is the leading determinant of students choosing a STEM-career. Using HSLS:09 data, one could investigate further science survey questions within the student's freshman and junior year in high school. These added statistics could narrow down specific information concerning science learning and future STEM-degree choices. This added knowledge would make high schools better equipped to prevent the decline of STEM majors in a post-secondary setting.
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Appendix A

Math Regression Figures

In chapter 4, it was noted that the scatterplots for the normal distribution for the independent variables and dependent variable would be listed for the math regression in Appendix A.

Figure 10
Normal Distribution 2009 Math Self-efficacy and Math Utility

Figure 11
Normal Distribution 2011 Math Self-efficacy and Math Utility
Figure 12
Normal Distribution 2009 Math Interest and Math Utility

Figure 13
Normal Distribution 2011 Math Interest and Math Utility
Appendix B
Science Regression Figures

In chapter 4, it was noted that the scatterplots for the normal distribution for the independent variables and dependent variables would be listed for the science regression in Appendix B.

**Figure 14**
*Normal Distribution 2009 Science Self-efficacy and Math Utility*

![Partial Regression Plot](image)

**Figure 15**
*Normal Distribution 2011 Science Self-efficacy and Math Utility*

![Partial Regression Plot](image)
Figure 16
Normal Distribution 2009 Science Interest and Math Utility

Figure 17
Normal Distribution 2011 Science Interest and Math Utility
Institutional Review Board
Division of Research and Innovation
Office of Research Compliance
University of Memphis
315 Admin Bldg
Memphis, TN 38152-3370

2020-10-27

PI Name: Audrea Barker
Co-Investigators:
Advisor and/or Co-PI: Karen Kitchens
Submission Type: Admin Withdrawal
Title: Does Immersion in a STEM-focused High School Lead to a STEM Major in a Post-Secondary Institution?
IRB ID: PRO-FY2021-137

From the information provided on your determination review request for “Does Immersion in a STEM-focused High School Lead to a STEM Major in a Post-Secondary Institution?”, the IRB has determined that your activity does not meet the Office of Human Subjects Research Protections definition of human subjects research and 45 CFR part 46 does not apply.

This study does not require IRB approval nor review. Your determination will be administratively withdrawn from Cayuse IRB and you will receive an email similar to this correspondence from irb@memphis.edu. This submission will be archived in Cayuse IRB.

Thanks,

IRB Administrator
Division of Research and Innovation
Office of Research Compliance
315 Administration Building
Memphis, TN 38152-3370
P: 901.678.2705
F: 901.678.4409