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College Students' Persistence and Degree Completion In Science, Technology, Engineering, and Mathematics (STEM): The Role Of Non-Cognitive Attributes Of Self-Efficacy, Outcome Expectations, And Interest

Michael Aryee
michael.aryee@student.shu.edu

COLLEGE STUDENTS' PERSISTENCE AND DEGREE COMPLETION IN SCIENCE, TECHNOLOGY, ENGINEERING, AND MATHEMATICS (STEM): THE ROLE OF NON-COGNITIVE ATTRIBUTES OF SELF-EFFICACY, OUTCOME EXPECTATIONS, AND INTEREST

By

Michael Aryee, MBA

Dissertation Committee:

Eunyoung Kim, Ph.D., Committee Chair
Robert Kelchen, Ph.D., Committee member
Rong Chen, Ph.D., Committee member

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Michael Aryee, has successfully defended and made the required modifications to the text of the doctoral dissertation for the **Ph.D.** during this **Spring Semester 2017**.

DISSERTATION COMMITTEE
(please sign and date beside your name)

Mentor:
Dr. Eunyoung Kim Kim Eun Young 3/13/17

Committee Member:
Dr. Robert Kelchen Robert K 3/13/17

Committee Member:
Dr. Rong Chen R Chen 3/13/2017

The mentor and any other committee members who wish to review revisions will sign and date this document only when revisions have been completed. Please return this form to the Office of Graduate Studies, where it will be placed in the candidate's file and submit a copy with your final dissertation to be bound as page number two.

Abstract

The lack of students' persistence (or student's effort to continue their academic studies until degree completion) in Science, Technology, Engineering, and Mathematics (STEM) and the attrition of STEM students as well as the shortage of STEM workers have gathered much attention from policy makers, governmental agencies, higher education researchers and administrators in recent years. As a result, much research efforts have been directed towards identifying factors causing the leaks in the STEM pipeline and finding effectively antidotes to patch the leakage points along the pipe. In the past, most studies in the STEM disciplines have focused on individual cognitive capacities (or academic predictors) such as precollege performance indicators (e.g., high school GPA) and standardized achievement test scores (e.g., SAT and ACT) to explain the leading factors contributing to the high attrition rate among STEM college students. Yet these studies just address mainly one aspect of the key reasons why students failed to persist. We still lack evidence, both empirically and theoretically, on how "*non-cognitive skills*"—which are essential individual characteristics vital for success in any schooling, work, and other life-time outcomes— may influence STEM major persistence. Absent from most of the scholarly discussions are the many ways in which psychosocial factors (such as grit, tenacity, optimism, self-efficacy, perseverance, motivation, self-discipline, teamwork, reliability) influence the decision-making processes of students' persistence. Rather than focusing on the traditional cognitive ability and academic achievement measures of academic preparation this study focused on psychosocial factors that influence the decision-making processes of students' persistence and degree completion.

The purpose of the study is to examine the extent to which non-cognitive factors (i.e., self-efficacy, outcome expectation, and interest) contribute to undergraduate students' persistence and college degree completion in STEM with particular attention to students enrolled in 4-year colleges and universities in the United States. The analytical sample for this study was drawn from the Educational Longitudinal Study (ELS:2002-2012) dataset with the final sample used for analysis representing the 2002 cohort of 10th graders who declared STEM major in college by 2006 and participated in the final wave of ELS in 2012. As such, the result was reflective of this group of students, and not all STEM students in college in general. Result of the study revealed three general findings about the three noncognitive factors. First, students with strong interest in pursuing a STEM major, a high sense of self-efficacy, and a mid to high level of outcome expectations are more likely to persist and complete their college degree in their declared major in STEM field. Students who reported that they had no interest in pursuing a STEM major yet declared a STEM major in their postsecondary education, and who have moderate to high self-efficacy and high outcome expectations are more likely to switch to a non-STEM major and persist to complete a degree in a non-STEM field. Thirdly, irrespective of whether the student was interested in pursuing STEM, a student with low self-efficacy and low outcome expectations was more likely to not attain any degree or credential.

But those who wait on the Lord

Shall renew their strength;

They shall mount up with wings like eagles,

They shall run and not be weary,

They shall walk and not faint.

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Table of Contents

List of Tables

Table Page

Table Page

List of Figures

CHAPTER I

INTRODUCTION

Nearly a decade ago, the chairman of the National Science Board, Steven C. Beering, stated in his memorandum to members of Congress that "…the Nation is failing to meet the Science, Technology, Engineering, and Mathematics (STEM) education needs of U.S. students, with serious implications for our scientific and engineering workforce in the 21st century" (National Science Board, 2007, p. v). Beering's remark, in part, may have arisen from the disappointing statistics concerning the large number of postsecondary students leaving the STEM field before graduation or by switching to non-STEM fields (Lowell et al. 2009; National Science Board 2012). Consequently, the U.S. may not be able to fulfill the increasing demand for domestic STEM workers nor sufficient STEM workforce to maintain its global leadership and its competitive edge in scientific innovations (U.S. Joint Economic Committee, 2012).

General background

Evidence of lack of STEM persistence and low retention rates

The recent body of STEM literature is filled with statistical evidence of the leaks in the STEM pipeline. Using the most recent data on students' attrition from STEM fields from the 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09) and its related database of 2009 Postsecondary Education Transcript Study (PETS:09), Chen (2013) showed that nearly half (48%) of STEM degree-seeking students who started college at a 4-year institution had left without being able to complete a bachelor's degree in a STEM discipline by 2009 (6 years after they began college). Chen (2013) also reported that nearly one-half of those that left the STEM major earned a degree in a non-STEM field, while the remaining half completely exited college without earning a degree or certificate.

For community colleges, the statistics was even more alarming as 69% of the 2003-starting cohort had left these fields at some point within the 6-year period after their initial enrollment without attaining any certificate, associate degree, or bachelor's degree with a STEM field credentials (Chen, 2013). While 59% of degree-seeking college students who began college in fall 2006 complete their degree within six years (Aud et al., 2014), only about 40% of STEM degree aspirants were able to complete their degree in the same time frame (Holden & Lander, 2012; Hurtado et al., 2012).

The attrition problem is even worse for historically underserved racial and ethnic minorities who continue to be severely underrepresented within STEM fields (National Science Foundation, 2011; U.S. Census Bureau, 2009; Griffith, 2010; George & Malcolm, 2011). In a survey of 200,000 students—who declared their first postsecondary major in the STEM disciplines—conducted by the Higher Education Research Institute (HERI, 2010), the study revealed that only 31% of African American students, 40% of Latino students, and 37% of Native American students completed their degrees in any major within five years compared to over 60% of their white counterparts. Similarly, although combined Blacks and Hispanics represent 30% of the total US population (U.S. Census Bureau's 2014 National Projections, 2014), only 8.4% of all the workers in STEM occupations are of Black (3.9%) or Hispanic origin (4.5%), compared to 77.3% who are Whites and 17.2% who are Asian Americans (National Science Foundation, 2011). Griffith (2010) concluded that African Americans and Hispanics are less likely to persist in STEM majors during college.

Data from the U.S. Department of Education (2011) estimates that only 7.5% of African Americans and 7% of Hispanics achieved a bachelor degree in STEM disciplines during the 2008-2009 academic year (U.S. Dept. of Education, 2011). Crisp and Nora, (2012) remarked that: “The demand for skilled workers in STEM fields will be difficult, if not impossible to meet, if the nation’s future mathematicians, scientists, engineers, information technologists, computer programmers, and health care workers do not reflect the diversity of the population” (p. 2). As America’s population continue to shift towards a greater share of people from racial/ethnic minority backgrounds, a growing concern about college completion rates of this population has risen to become a national issue.

Many state and federal leaders and academic researchers have paid close attention to the need for the United States to improve the college degree attainment rates of students in the STEM fields if the nation is to continue to maintain its global competence (Bettinger 2010; Callan 2008; Freeman 2006; Lowell et al. 2009; Zumeta & Raveling 2002). The President’s Council of Advisors on Science and Technology (PCAST) has estimated that the U.S. will need to produce one million new college graduates in STEM fields in order to maintain the country’s global economic advantage (PCAST, 2012). To remain globally competitive in the future, the United States will need to increasingly develop more of STEM talents and sustain the constant flow of highly skilled scientists and engineers emanating right from its own universities and colleges (Ehrenberg 2010; National Academy of Science 2005; National Governors Association 2007; National Research Council 2012; National Science Board 2007; President’s Council of Advisors on Science and Technology 2012; Sullivan 2006; Xie & Killewald 2012).

As concerns about the relatively low college graduation rates in the STEM disciplines continue to grow and threaten to weaken the nation's supply of qualified STEM graduates to the STEM workforce, a number of empirical research studies have been conducted, at least, to examine the factors associated with the lack of student persistence and attrition in the STEM fields (Berkner & Choy 2008; Bettinger 2010; Espinosa 2011; Ost 2010; Radford & Horn 2012; Rask 2010; Seymour 2001; National Science Board, 2015). The central focus of these studies are represented in the following section.

Research studies on factors predicting persistence in college

Previous studies have examined the causes of student attrition—and especially in STEM, primarily focusing on individual cognitive capacities (i.e. academic predictors) such as precollege performance indicators (e.g. high school grade point average (GPA)) and standardized achievement test scores (e.g. SAT and ACT) to explain key factors attributable to the high attrition rate among college students (Braxton, Hirschy, & McClendon, 2004; Daley, 2010; Glogowska, Young, and Lockyer, 2007; Johnson, 2006; Tinto, 1993). Several researchers have come to conclusion that students' pre-college academic preparation (based on the existing cognitive measures of academic preparation) was one of the key reasons as to why students failed to persist (e.g., Nicholls, Wolfe, Besterfield-Sacre, Shuman, & Larpkiattaworn, 2007; Sadler et al., 2012; Veenstra, Dey, & Herrin, 2008). As Johnson (2006) noted, students' "grade performance… has been shown to be the most important factor in college persistence and eventual degree attainment" (p. 927).

Using existing cognitive measures of academic preparation to determine college persistence seemed to be logical at the time when the use of standardized testing as a selection tool for determining college acceptance was deeply rooted in the nation’s long standing history of preferring a meritocratic caste system over a privileged class system of selection (Lehman, 1999, Robbins, Davis, Lauver, & Langley, 2004). College admissions personnel assess students’ potential to succeed academically and to graduate eventually in college based on standardized cognitive measures of academic preparation such as the SAT and ACT.

Traditionally, these cognitive measures of academic preparation (high school GPA, SAT, ACT, etc.) have assumed some degree of predictive validity in determining student’s success and persistence in college (Grissmer, 2000; Scott-Clayton, 2012). Although the predictive power of these variables varies between similar studies, Astin and his colleagues (1987) showed that high school GPA and SAT/ACT test scores account for about 12 percent of the variation in college retention. In another study, Tross and his colleagues (2000) reported that these two variables account for about 29 percent of the total variation in student’s retention.

Several studies have consistently showed association of high school GPA and test scores on standardized SAT/ACT achievement tests with academic achievement and persistence in college (ACT Research Report Series, 2012; Johnson, 2006; Noble & Sawyer, 2004; Patterson et al., 2012; Zwick & Sklar, 2005). For instance, ACT Research Report Series (2012) found that students with high high school GPA demonstrate significant long-term academic persistence compared to those with low high school GPA. Since high school GPA and test scores on standardized achievement tests are highly correlated, it is difficult to be certain which one of the two is more powerful, although most studies point to high school GPA as the stronger predictor (Hanover Research, 2011).

Among African American and Hispanic students, it has been found that student's academic performance such as high school GPA (Herrera and Hurtado, 2011) and standardized test scores such as SAT (Garcia and Hurtado, 2010) influence college persistence in STEM fields. Other studies have also identified students' grade as the most significant determinant of student persistence (ACT Research Report Series, 2012; Pascarella and Terezini, 2005). Crisp, Nora, and Taggart (2009) found that students' SAT math score and high school class rank percentile decisions was strongly associated with student's decision to earn a STEM degree at a Hispanic-serving institution.

In addition to the cognitive and academic achievement variables such as high school GPA and SAT/ACT test scores, an overview of existing literature also revealed student's entry characteristics and demographic variables such as gender, race/ethnicity as well as socio-economic status as standard predictors of student persistence and retention behavior (Lotkowski, Robbins, & Noeth, 2004; Chen, 2013; Pascarella & Terenzini, 2005; Reason, 2009; Walpole, 2003). These studies indicate that race/ethnicity and gender are two most consistent predictors of student persistence and retention. Most of the studies show that female students persist to degree completion at higher rates than their male counterparts. Other research also identified race/ethnicity as a significant factor in predicting student persistence (Pryor and Hurtado, 2012). Reason (2009) however, cautioned that the relationship between each of these two variables (gender and race/ethnicity) and persistence is complex. Reason (2009) found that gender tends to be statistically insignificant predictor when other important predictors such as socio-economic status is controlled in the model.

Institutional and environmental characteristics such as the quality of students' interaction with faculty, advisors, and peers, students' sense of belonging, their involvement in social life of campus, access to campus supportive networks, prevailing culture on campus environments, just to mention a few, also shape students' persistence behavior (Berger & Heath 2005; Flowers 2003; Strayhorn 2012; Nora, 2003; Pryor & Hurtado, 2012; Veenstra, 2010; Zhao et al. 2012).

Scholarly literature on STEM persistence abounds with references to three main categories of traditional factors that have been identified as important in this area of study. The variables include (a) student demographic background (e.g., gender, socio-economic status, and parental educational level), (b) student cognitive and academic characteristics (e.g., high school GPA, math and science standardized test scores including SAT scores, and the number of Advanced placement (AP) course taken), and (c) environmental and institutional factors (e.g., sense of belonging, involvement in social life of campus, access to campus supportive networks, prevailing culture on campus environments, degree of selectiveness of postsecondary institution, etc.) (Flowers 2003; Strayhorn 2012; Berger & Heath 2005; Zhao et al. 2012; Nora, 2003; Veenstra, 2010).

Statement of the Problem

Many researchers have investigated the predictability of cognitive variables (academic and intellectual abilities) that influence students' retention while controlling for students' demographic, background and contextual characteristics. Over the past several decades, most of the explanations given for the high dropout rate experienced by undergraduate institutions are usually based on Tinto's (1987, 1993) theory of student integration model— which is one of the most widely cited theories of student persistence in the field of higher education to the extent that it has been described by some researchers as reaching the level of “paradigmatic stature” (Braxton & Lee, 2005, p. 108).

However, little focus has been given to empirically investigating non-cognitive skills and attitudes, behaviors, and strategies during the high school experience that may influence students’ success in their postsecondary education and later in their workplaces. Absent from most of the scholarly discussion are the ways in which psychosocial factors influence the decision-making processes of students’ persistence. Grit, tenacity, realistic optimism, self-efficacy, self-regulation, perseverance, interest, motivation, self-discipline, outcome expectations, reliability, such terms generally lumped under the category “non-cognitive skills”—which are essential individual characteristics vital for success in any schooling, work, and other life-time outcomes —are often excluded from the set of explanatory variables of most of the studies on STEM major persistence (Ackerman, Kanfer, & Beier, 2013).

Yet, non-cognitive behaviors and personal attributes—which are seldom used to assess students’ academic performance and persistence—have been found to be highly positively associated with academic success in college, occupational attainment and earnings (Guiffrida, 2006; Richardson, Abraham, & Bond, 2012; Jencks, 1979; Poropat, 2009; Robbins et al., 2004; Reason, 2009). Recent reported indicate that about 41% of the variation in student performance is predicted by affective variables such as student motivation, self-regulation, and assertiveness (Zientek, Ozel, Fong, & Griffin, 2013). Not only do such skills help students to identify the right courses to enroll in, but also would help higher education administrators in designing appropriate interventions for improving student retention and success (Kahn, Nauta, Gailbreath, Tipps, & Chartrand, 2002). Some recent studies have provided insight into the predictive power of non-cognitive characteristics over cognitive attributes in predicting student retention and academic achievement (Burner, 2005; Rosen, Glennie, Dalton, Lennon, & Bozick, 2010).

Robbins et al. (2004) conducted a meta-analysis using 109 studies to examine the relationship between non-cognitive (non-academic) and academic factors and postsecondary retention. They identified nine psychological constructs in the non-academic category (academic goals, achievement motivation, academic self-confidence, academic-related skills, contextual influences, general self-concept, institutional commitment, social support, and social involvement), two academic factors (high school GPA and ACT score) and student's socioeconomic status (SES) that influence retention. They found that, with the exception of general self-concept and achievement motivation which had a weak relationship, all the variables in the model accounted for a moderate to strong positive relationship to retention. Academic self-confidence and academic goals were the strongest predictors of retention. Their findings suggest that solely relying on traditional cognitive attributes may not be sufficient to predict college persistence and incorporating non-cognitive students' attributes to the prediction model may increase the predictive power of college persistence.

Moreover, researchers have begun to acknowledge that the content knowledge and academic skills model of determining academic performance and persistence is no longer sufficient to adequately address or explain student outcome differences (Baxter, 2004; Ackerman & Kanfer, 2013). A study, for example, found that a student's competence beliefs, defined as a perception of how good a student think he or she is at a given activity, can be regarded as a key predictor of academic performance and persistence (Freiberger, Steinmayr, & Spinath, 2012). Scherer (2013) noted that, for individuals in the scientific fields, competence beliefs—which is also referred to as self-concepts and self-efficacy—play an important role in achieving their learning objectives, solving problems, and improving general academic performance (Mason et al., 2013; Scherer, 2013; Tsai et al., 2011; Van Dinther, Dochy, & Segers, 2011).

Richardson et al. (2012) used a meta-analysis of 7,167 studies conducted between 1997 and 2010 to examine the relationship between academic self-efficacy, self-concept, effort regulation, goals for course grades, locus of control, and other personality traits and college GPA and found that these attributes accounts for 14% of variance in college grades. Another meta-analysis by Schmidt and Hunter (1998) also confirmed that non-cognitive skills accounted for about 20% improvement in predicting training accomplishment and job productivity (Schmidt & Hunter, 1998), pointing to the importance role non-cognitive skills in improving the prediction of student persistence.

Thus, the role of non-cognitive skills is largely unexamined in the STEM persistence literature. Given that this area of research has been vastly overlooked in the literature, there is the need to investigate the relationship in order to better understanding its impact on higher education persistence. Clearly, a notable gap exists in the literature regarding how non-cognitive skills during high school may contribute to students' postsecondary persistence and eventual degree completion, especially with regard to students in STEM courses. Very limited literature to date have attempted quantitatively to measure the impact of non-cognitive factors during high school years on the persistence and degree completion of students in STEM disciplines within a theoretical framework that controls for variables that previously have been identified to be related to college access and success.

Identification of Variables and Conceptual Framework

Recognizing that the extant literature revealed mostly the importance of pre-college preparation, high school performance, and cognitive (academic and intellectual) measures of ability to predict the success and persistence of students pursuing STEM degrees, it has become apparent that the traditional models of predicting students' successful completion of college may no longer be adequate in explaining student persistence and degree completion. The traditional cognitive predictors do not account for the underlying motivational, affective, and psychological processes that both contribute to and influence student's persistence behavior (Bean, 2005; Schreiner & Louis, 2011). It seems reasonable to search for alternate models that would incorporate a wide range of factors such as students' beliefs, attitudes, personality and motivational traits, values and expectations which are not specifically intellectual or academic in nature.

To better understand the role that student's high school non-cognitive attributes and skills play in their later persistence and degree completion in STEM majors in college, this study draws upon a set of concrete and empirically supported social cognitive variables from the key constructs of the Social Cognitive Career Theory (SCCT) framework (see Figure 1). These variables in the SCCT consider multiple and interrelated social cognitive variables (e.g., self-efficacy, outcome expectations, and interests) as well as other factors such as learning experiences, background characteristics, and contextual influences. The full model of the SCCT framework from which key non-cognitive constructs and structural relationships were extracted for this study is presented below in figure 1.

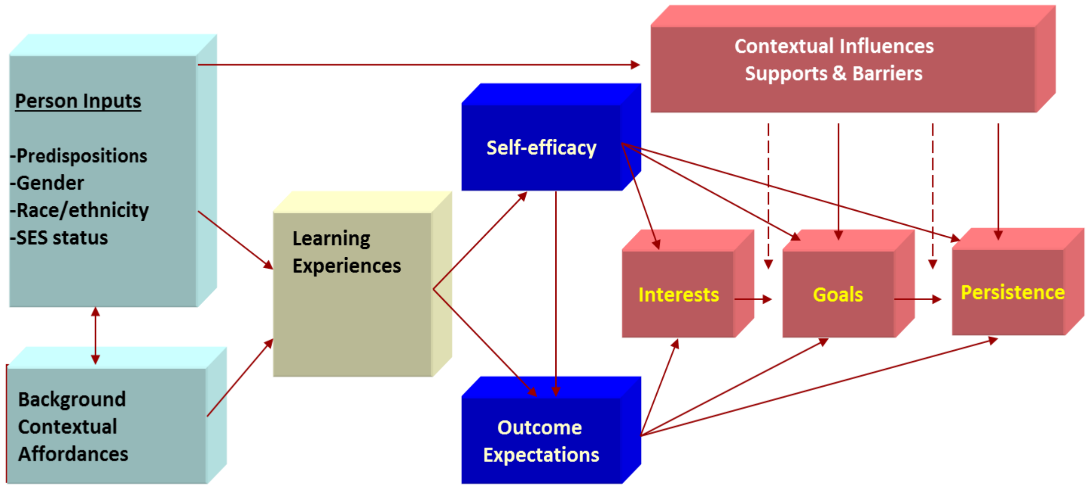

Figure 1. SCCT (Lent, Brown & Hackett, 1994, 2008, 2015)

According to Lent, Brown, & Hackett (1994)—the developers of the SCCT framework, the SCCT, which evolved from Bandura's Social Cognitive Theory (SCT) —the SCCT focuses on "(a) formation and elaboration of career-relevant interest, (b) the selection of academic and career related choice options, and (c) performance and persistence in educational and occupational pursuits" (Lent et al., 1994, p. 79). In general, the SCCT explains the processes that occurs within educational and occupational pursuits by examining three interconnecting models of how individuals' career interests develop, how they make career and educational choices, and how they persist and achieve academic and career success (Lent, Brown, & Hackett, 1994, 2000).

The SCCT is useful in deconstructing and understanding how individuals make career and educational choices, how they develop career and educational interests, how they deal with barriers and support that come their way in their educational and occupational pursuits, as well as how they persist and achieve academic and career success. One unique feature of the SCCT framework is its focus on the psychological processes that influence individual choices and actions. Most studies using the SCCT framework emphasizes the social cognitive constructs of self-efficacy, outcome expectations, interest, goals (Lent, Brown, & Hackett, 2000).

The SCCT proposes that students who fare well and persist in college and eventually graduate do so because, in addition to their academic performance and contextual learning experiences, they have a strong robust academic self-efficacy and a context-specific personal expectation (positive outcome expectation) which help them hold high commitment (high interest and goals) to their chosen academic or career field. Such high commitment motivates students to respond to their obligations and responsibilities with vigor, resilience and perseverance—not to succumb to obstacles, distractions, and occasional setbacks that easily overwhelm their peers. The mediating influence of self-efficacy and outcome expectations encourage students not to avoid academic challenges but to attack them head on and to put effort into their academic studies.

In terms of college persistence, the theory proposes that students are more likely to persist to graduation when they actively pursue and make progress at personally valued goals (performance goals and interest), if they feel competent and confidence in their ability to accomplish these goals (self-efficacy), if they anticipate receipt of favorable outcome (outcome expectations), and finally, if they perceive the environment as supportive and offering the resources they need to pursue their goals and interest (contextual factors) (Lent, Brown, & Hackett, 1994, 2000).

This study therefore identified five key constructs from the SCCT framework that relevant to STEM persistence and degree completion. The first three constructs paralleled similar variables in the traditional model and they are: (1) *Person/background inputs* which are represented by the inclusion of gender, race/ethnicity, socioeconomic status, and prior academic performance such as high school grade point average (2) *Contextual and environmental supports and barriers* which are factors that encourage or impede the attainment of students' overall goal (e.g., academic integration, and institutional selectivity). The remaining three constructs which were usually not addressed by the traditional models are: (3) *Self-efficacy* which refers to one's belief about his or her ability to perform and accomplish an academic task successfully (e.g., feeling confident that one has the ability to complete the tasks required for successful performance), (4) *outcome expectations* which is a belief about the consequences or the results of engaging in academic task—e.g., anticipating receipt of favorable outcome, and (5) *interest* which refers to the extent to which one likes the academic activity—e.g., actively pursuing and making progress at personal valued goals.

As SCCT continues to be applied to persistence of students within the STEM disciplines (e.g., Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Lent et al., 2013; Lent et al., 2005; Lent et al., 2008; Lent, Brown, et al., 2005; Lent, Singley, Sheu, Schmidt, & Schmidt, 2007; Lent, Sheu, & Lopez, 2011; Mullikin, Bakken, & Betz, 2007), each of the above-mentioned variables have been empirically demonstrated to relate directly or indirectly to STEM persistence. Three of the key constructs of SCCT—*Self-efficacy, outcome expectations*, and *interest*, which have survived years of rigorous research and have proven relationship with STEM persistence and degree completion—would serve as the non-cognitive variables for this study. Thus, the current study focused mostly on these three-core construct of the SCCT— *Self-efficacy, outcome expectations*, and *interest* as the key non-cognitive variables of this study.

Purpose of the Study

This study examined the extent to which non-cognitive factors (i.e., self-efficacy, outcome expectation, and STEM interest), students' demographic/background characteristics (e.g., gender, ethnicity, socio-economic status, and high school GPA) and students' contextual and environmental characteristics (e.g., academic integration, and institutional selectivity) contributed to and influenced undergraduate students' persistence and college degree completion in Science, Technology, Engineering, and Mathematics (STEM) with particular attention to students enrolled in 4-year colleges and universities in the United States.

In this study, STEM persistence and college degree completion was conceptualized as a three-part categorical variable corresponding to students' bachelor's degree completion status, six years after declaring a major in a STEM field at a four-year postsecondary institution. These are: (1) STEM degree earners (i.e., students who earned at least a bachelor's degree or higher in STEM field), (2) non-STEM degree earners (i.e., students who changed their majors and completed at least a bachelor's degree or higher in a non-STEM field), or (3) no degree earners (students who had not completed a degree).

The research so far suggests that a student's high school non-cognitive attributes (self-efficacy, outcome expectation, and interests, key constructs in the SCCT), demographic/background characteristics (e.g., gender, ethnicity, socio-economic status, and high school GPA) and students' contextual and environmental characteristics (e.g., academic integration, and institutional selectivity) may be strongly linked to their persistence and bachelor's degree completion in STEM majors in college.

Research Questions

In this study, I explored the following research questions:

1. Are there any differences in self-efficacy by STEM persistence and degree completion status?
2. Are there any differences in outcome expectations by STEM persistence and degree completion status?
3. Is there a relationship between STEM interest and STEM persistence and degree completion status?
4. To what extent, if any, do students' demographic/background characteristics (e.g., gender, ethnicity, socio-economic status, and high school GPA) and students' contextual and environmental characteristics (e.g., academic integration, and institutional selectivity) affect their STEM persistence and degree completion status?
5. Controlling for demographic and background characteristics and students' contextual and environmental characteristics, to what extent do individuals' non-cognitive attributes (i.e., self-efficacy, outcome expectations, and STEM interest) contribute to STEM persistence and degree completion status?

Significance of the Study

Although much work has been done in the area of identifying students' academic and cognitive profiles to help make predictions on their performance and persistence in postsecondary education, the same cannot be said about the noncognitive profiles of students.

Identifying student’s noncognitive attributes might help postsecondary administrators in developing critical intervention and support systems for students who may lack certain noncognitive characteristics which affect persistence. As most higher education continues to face severe financial challenges, the significance of identifying factors that influence persistence will play an important role in the success of the postsecondary institutions (Altbach, Gumport, & Berdahl, 2011; St. John & Chen, 2011; Johnstone, 2011).

Ackerman, Kanfer, and Beier (2013) observed that the attrition of students in the postsecondary education sector may be due to failure to identify students’ noncognitive characteristics and provide intervention for students at risk. Both cognitive and academic and non-academic factors play an important role in fostering student success and persistence (Ackerman, Kanfer, and Beier, 2013).

It is also known that America’s global competitive edge depends heavily on skills acquired through the study of STEM disciplines (U.S. Joint Economic Committee, 2012). The national economic and social benefit for increasing the number of students earning a STEM degree can be substantial if the U.S. can find solutions and interventions for the problems affecting students’ persistence in STEM major fields. At the individual level, college graduates with STEM degrees earn far more than their non-STEM counterparts. Recent data show that STEM workers earn about 26% more than their non-STEM colleagues (White House Fact Sheet, 2010). Increasing the minority pool will increase minority access to these high paying jobs as well as reduce the income inequality between the two groups. At the national level, increasing the number of STEM graduates is vital to the advancement of the U.S. in the global competitive knowledge driven economy. Broadening the pool of STEM students by increasing the number of minority students in STEM will help maintain our competitiveness on global market.

There are a number of potential benefits to be gained if the predictive base of students' persistence in STEM major fields is broadened beyond and above the traditional cognitive predictor spectrum. For example, new knowledge obtained from identifying the important non-cognitive predictors of persistence will generally help the postsecondary community in developing more effective persistence models for the future. In addition, identifying and analyzing non-cognitive predictors will help postsecondary educators and school administrators to create strategies which allow for targeted and personalized learning and offer opportunity for institutions to crystallize their programs and improve their student advisory services. It will also help them to make more informed policy decisions. In other words, identifying the important non-cognitive predictors of persistence will provide policy makers with understanding of the how specific non-cognitive factors influence minority student success and persistence in STEM. This study therefore will help advance the predictive knowledge in the area of STEM field persistence as well as help university administrators and policy makers in identifying areas in which they can support and improve on.

Definitions

The following terms are commonly used throughout the present study:

- ***The National Science Foundation definition of STEM*** includes the following disciplines: Engineering, Physical Sciences, Mathematics and Computer Sciences, Life/Biological Sciences, Social/Behavioral Sciences (Economics, Psychology and Social Sciences).
- For the present study, **STEM** will be defined as any subject that uses and applies academic concepts in science, technology, engineering, and mathematics to real-world situations in contexts that make connections between academic knowledge and real-world phenomena (Author). For the sake of this study, the operational definition of STEM is: Engineering, Physical Sciences, Mathematics and Computer Sciences, Life/Biological Sciences.
- **STEM Persistence:** The ability for students who enter a postsecondary institution with declared STEM subject to continue their STEM education until they earn at least a bachelor's degree in STEM.
- **STEM persisters** are a subgroup of students who entered postsecondary education in STEM fields and remain in STEM fields throughout their college career.
- **STEM leavers** are a subgroup of STEM entrants who leave STEM fields. These include those who switch their major to a non-STEM field and those who left postsecondary education without earning a four-year degree.
- ***STEM attrition*** refers to the enrollment choices that result in potential STEM graduates (i.e., undergraduates who declare a STEM major) moving away from STEM fields by switching majors to non-STEM fields or leaving postsecondary education before earning a degree or certificate.

- **Persistence** and **Retention:** It is also important to note the difference of these two terms, persistence and retention. Although they both refer to the same concept, that is, of staying at a postsecondary institution until a degree or a certificate is earned, **retention** does not capture the student decision making process nor does it account for factors which cannot be controlled by the institution and its practices. On the other hand, **persistence** captures all institutional and external factors which influence a student's desire to remain at an institution.

CHAPTER II

REVIEW OF LITERATURE

Introduction

This review of literature will provide insight about the key concepts, theoretical framework, and related literature on persistence of students in STEM major fields (Part I) and the Social Cognitive Career Theory (SCCT) (Part II). The review will begin with the concept of noncognitive classifications and will proceed by exploring three major retention and persistence theories. After reviewing these major models, it will explore the gaps in the major retention and persistence theories in order to justify the need for a model that incorporates non-cognitive variables.

Following this section, the study will provide detailed explanations about the Social Cognitive Career Theory (SCCT) (Lent, Brown, & Hackett, 1994, 2000). This is a psychosocial model, which is inclusive of behavioral, psychological, social and demographic variables. The SCCT, which is usually found in the career-development literature, will provide the conceptual clarity needed to explain college students' persistence, especially in the STEM fields. The SCCT captures the theoretical rich constructs of cognitive and non-cognitive factors that influence the way people develop career interests, make choices, performance behaviors and how they achieve educational and occupational success as they pursue their educational or occupational goal (Lent et al., 1994).

Next, the study will use the factors in the SCCT theoretical model to propose a modified model for this study. Again, this study will focus on three of the core construct of the SCCT—Self-efficacy, outcome expectations, and interests. The study will also discuss other research that confirm or refute the predictive ability of each the focused factors. Also, the study will explore the relationship between these factors and STEM persistence.

The non-cognitive Classification

The term “noncognitive” skills (or attributes) require some clarification. It usually appears in the literature either as one word (noncognitive) or hyphenated (non-cognitive). It also comes under several synonyms such as psychological, psychosocial, non-academic, non-intellectual, or behavioral attributes. It is generally used to express individual skills and personality traits that are not in the cognitive domain. In this context, cognitive abilities are usually associated with intellectual capacity, reasoning, and ability to understand and solve abstract problems. Measures of cognitive skills include the use of intelligence tests and the standardized tests, especially on reading, science and math (Ackerman, 1996).

Since the early 1970s, the “noncognitive” terminology has been very common in the extant literature. Its usage mostly encompassed a broad spectrum of personality attributes. It is usually expressed in two forms, either psychological in nature (e.g., goals, interest, motivation, satisfaction, self-efficacy, etc.) or behavioral (e.g., interpersonal skills, participating in extracurricular activities, self-discipline, honesty, integrity, etc.). Borghans et al. (2008) described noncognitive skills as the “pattern of thoughts, feelings and behavior” (p. 974). Heckman (2008) listed noncognitive skills to include motivation, the ability to work with others, socio-emotional regulation, personality factors and time preference. Thus, noncognitive skills consist of the psychological and behavioral dispositions and tendencies that are not typically assessed through cognitive measures such as intelligence tests or the standardized tests. In most cases, the list selected for a particular study is often dictated by the availability of data.

One weakness of using noncognitive variables in a study is the fact that the information obtained is usually self-reported in nature. Apart from the difficulty in measurement, concern has also been raised about the confusing demarcation of the term cognitive and noncognitive category (Borghans et al., 2008, and by Almlund et al., 2011). For this reason, most studies focused mainly on cognitive characteristics using mainly content knowledge to determine persistence.

However, recent researches have shown that using content knowledge and cognitive approaches to understand student persistence without taking into consideration the richer set of personality traits and skills (often referred to as affective characteristics) that aided and motivated the student in the acquisition of the content knowledge and cognitive skills is not sufficient. For example, in their first year of college, students may still be dealing with a variety of internal issues, such as their own changing identity, the future of their education, and interpersonal and internal conflicts. Within the same context, they are expected to complete homework, pass their tests, and be socially responsive. Students therefore must rely on their own acquired and innate psychological resources and personality attributes such as grit, tenacity, motivation and perseverance to overcome external challenges and to persevere in their chosen majors.

Non-cognitive characteristics, therefore, in the context of this study, refer to the attitudes, dispositions, social skills, and interpersonal skills that the student draws upon to enable the accomplishment of their academic goals and to navigate successfully through the academic climate. These attributes together with other social roles and cultural determinants constitute the personality of an individual. They determine how an individual student would personally respond to various tasks and challenges. Non-cognitive characteristics therefore, may focus on behaviors and attitudes that determine whether the student has personal interest in a learning activity and whether student persist in the face of difficulties and challenges.

Review of Major Persistence Models

Identifying the factors that influence the loss of students prior to completing a degree or those factors that determine the likelihood of persisting to degree attainment have long been of interest to numerous academic scholars (Amelink & Creamer, 2010; Adelman, 1998; Bonous-Hammarth, 2000; Cole & Espinoza, 2008; Crisp, Nora, & Taggart, 2009; Griffith, 2010; Seymour & Hewitt, 1997; Tinto, 1987; Zhao et al. 2012; Nora, 2003; Veenstra, 2010). Studies focusing on investigating the loss of students prior to completing their degree and college students' persistence— which generally refers to the student's continuation desire and behavior to stay within the education system through their degree completion—dates back to several decades (Spady, 1970; Bean, 1980). Early studies, especially those around the first half of the twentieth century, focused mainly on factors that influence students' cognitive intelligence and academic readiness. The early part of the twentieth century was characterized by the lack of full-blown theoretical models to explain the logic and the order behind the array of variables proposed to influence retention and persistence of college students (Spady, 1970).

Over the course of the second half of the twenty-first century, research efforts started to shift more towards the development of theoretical models to guide research and analysis of the potential variables used in explaining retention and persistence. The models of Spady (1970), Tinto (1975, 1983), Astin (1983), Bean (1980), just to mention a few, represent some of the early full-scale models that appeared in the student retention and persistence literature during the second half of the twenty-first century.

Spady's (1970) Model of the Dropout process

Spady (1970) was the first to introduced a full-scale theoretical model of student dropout in his "Explanatory Sociological Model of the Dropout Process" (Spady, 1970). Spady (1970) thought that there is the need for a "more interdisciplinary-based, theoretical synthesis of the most methodologically satisfactory findings and conceptually fruitful approaches to this problem [of dropout]" (p. 64). Spady therefore, proposed the first full-blown model to study the attrition and persistence problem. His model was based on Durkheim's (1951) influential work on suicide. Durkheim's (1951) idea was that an individual's likelihood of committing suicide can be reduced when that person has shared group values and friendship support. Spady (1970), incorporated these two variables from Durkheim (1951) into his model. Spady (1970) proposed that family background characteristics, academic potential, grade performance, level of intellectual development, shared group values, friendship support and normative congruence all contribute to increase social integration. Social integration increases satisfaction, which also in turn increases institutional commitment leading to a reduced likelihood of dropping out from college.

Tinto's Student Integration Model

Another full-scale theory that was also based upon the selected variables from Durkheim's (1951) theory and also built upon Spady's (1970) model was published by Vincent Tinto (1975) in 1975. Tinto's (1975) model by far, is the most widely empirically tested model of persistence and dropout process (Pascarella, 1980). Tinto reasoned that if people who break away from their social ties are usually the ones who lack social integration with the large society and are more susceptible to suicide, then it makes sense to believe that students would voluntarily withdraw from their educational community if they are not socially integrated into it.

Tinto (1975) proposed that a plethora of background characteristics (gender, race/ethnicity, family demographics and socio-economic status, precollege educational attainment, and personal skill sets) interact with each other to form the backbone of the individual's initial goal commitment and institutional commitment. Tinto (1975) argued that "the process of dropout from college can be viewed as a longitudinal process of interactions between the individual and the academic and social systems…which lead to persistence and/or to varying forms of dropout" (p. 94). Tinto (1975) envisaged two systems within the institution—the academic system and the social system. In the academic system, Tinto proposed that students' initial goal commitment may improve their grade performance and raise the level of their personal development, all together leading to academic integration and in a circular fashion reinforcing a greater goal commitment. Greater goal commitment reduces the likelihood of a student dropping out of college. Goal commitment is therefore placed twice within Tinto's (1975) model.

Within the social system, Tinto (1975) proposed that institutional commitment would impart positively on the interaction between students and their peers (peer-group) as well as with faculty members, which in turn would lead to an increase level of social integration, reinforcing institutional commitment once again, thus, leading to a reduce likelihood of dropping out. Institutional commitment is also placed twice within Tinto's (1975) model. Bean (1981) explained that the initial goal and institutional commitment are based on student's educational plans rather than the actions that they take to execute the plans. The latter is based on students' interaction with the social and academic systems of the institution.

Bean's Student Attrition Model

Another investigator who proposed a retention theory in the early 1980s was Bean (1980), who derived his model from the theoretical concepts of employee turnover in organizations, an idea borrowed from Price's study of worker turnover. Price's view was that income influences job satisfaction, which is a strong indicator of employee turnover. Bean (1980) found that the correspondence between income and job satisfaction can be similar to the correspondence between academic grades and achievement and dropout. Bean found that GPA was statistically linked to student's satisfaction, which in turn leads to institutional commitment. Bean (1980) disagreed with the use of Durkheim's suicide theory because the evidence of the theory, in Bean's estimation, was insufficient to establish a full-scale theoretical relationship between attrition and suicide. He therefore criticized both Tinto and Spady for providing models that lacked directional causality and discreteness, and concluded that any empirical studies employing these models may be inconclusive.

Bean (1980, 1983) then postulated that various student background characteristics, organizational variables, students' academic and social interaction directly influence satisfaction. This in turn influences institutional fit and commitment to degree completion leading to student's intent to leave and persistence (Bean 1980, 1983). Additionally, Beans Model of Student Attrition stressed on the existence of an external factors which the institution has no control over such as time spent away from campus, students' financial constraints, family commitments, and transfer opportunities. Bean explained that the combination of external factors, attitudinal influences, and interaction factors can collectively lead directly to a decision to drop out or to persistence.

Critique of the major Theories

Despite the prominent contribution of Tinto's and Bean's models in understanding students' departure, these models do not appear to have recognized the influence of students' psychological orientation on their persistence decisions (Guiffrida, 2006). Kahn and Nauta (2001) noted that the early traditional models explained only part of the variance of student persistence and has important limitations. Several researchers (e.g., Attinasi, 1989; Stage and Hossler, 2000; Hossler, 2005; Guiffrida, 2006) noted that these models focused heavily on integration and interaction and relied less on the pre-entry psychological factors which might have shaped and influenced the student's integration and interaction experiences. Robbins et al. (2004) reported that, although at the time of the development of these theories there were "theoretically rich constructs [available] with adequate internal and external validity," the models did not seem to have taken advantage of such research (p. 263). The authors recognized that a full understanding of college student persistence is lacking due to the "little of integration or research synthesis of the educational and psychological literature" (p. 261).

In order to increase understanding of the college persistence, Reason (2009) recommended incorporating student motivational and behavioral variables into the set of predictors for a better understanding of the college persistence puzzle. Ackerman, Kanfer, and Beier (2013) identified another major limitation of these models by reporting that:

> Although [these] models have been developed and evaluated to predict post-secondary student attrition (e.g., Tinto, 1975), they tend to focus on the entire "system" involved in undergraduate education (e.g., family background, peer and faculty interactions, institutional commitment). However, *individual attributes* represent a small part of these systems, and attributes other than intellectual ability have merely been suggested as potential influences. (p. 912)

Thomas, Kuncel, and Crede (2007) argued that, noncognitive variables such as maturity, motivation, self-concept, interpersonal skills, personality variables and other measures such as biographical information, personal interviews, and letters of recommendation can add validity to the traditional cognitive predictors. Recognizing that the traditional models of predicting students' successful college completion are no longer adequate in explaining student persistence, it seems reasonable to searched for other models that would incorporates a wide range of students' beliefs, attitudes, personality, motivational traits, values and expectations which are not specifically intellectual or academic in nature.

One such theoretical model, which has constructs that is inclusive of behavioral, psychological, social and demographic variables and that will provide the conceptual clarity needed to explain college students' persistence, especially in the STEM fields, was found in the career-development literature. The Social Cognitive Career Theory's (SCCT), developed by Lent, Brown, and Hackett (1994, 2000), captures the core non-cognitive attributes that influence the way people develop career interest, make choices, perform behaviors and achieve educational or occupational success as they pursue their educational or occupational goal (Lent et al., 1994). Thus, SCCT model explains how people make career choices and academic decisions. The SCCT is an appropriate model for looking at student persistence in postsecondary education since it incorporates the impact of the psychological, social, and contextual factors that influence undergraduate student retention which was largely missing from the major persistence studies (Allen & Robbins, 2008; Byars-Winston & Fouad, 2008; Lent et al., 1986; Lent, Brown, Sheu et al., 2005; Porter & Umbach, 2006). Kahn and Nauta, (2001) reported that the SCCT focuses on students' "intrapersonal factors and self-focused perceptions" (Kahn & Nauta, 2001, p. 635).

The Social Cognitive Career Theory (SCCT)

The Social Cognitive Career Theory (SCCT) was developed by Lent, Brown, and Hackett (1994). It represents an extension of Albert Bandura's (1986) Social Cognitive Theory which has been adapted to explain the processes and mechanisms through which "(a) career and academic interests develop, (b) career-related choices are forged and enacted, and (c) performance outcomes are explained" (Lent, Brown, & Hackett, 1994, p. 80).

Although the SCCT originally composed of the above three segmental models (interests, choice, and performance models), a fourth model (the satisfaction model) have been recently added by Lent and Brown (2006) which explores specific domains of occupational and educational *satisfaction* as well as other aspects of positive adjustment to academic and career related behaviors (Lent and Brown, 2006, 2008; Lent et al., 2013). According to Lent et al. (2013), although “SCCT's segmental models each focus on a particular class of academic and career outcomes, the models were designed to overlap with one another” (p. 23). The authors explained that all the models have common cores which consist of the social cognitive theory elements: self-efficacy, outcome expectations, and goal representations.

By building on Bandura’s (1986, 1989) Social Cognitive Theory, the SCCT underscores the mutual, dynamic, and interactive influences between *person inputs* (internal, affective states, biological and physical attributes), their *behavior* (individual choices and actions), and their *environment* (physical and social surroundings) (Bandura, 1986, 1989). Bandura (1986, 1989) used the term “*triadic reciprocity*” to describe the triadic, dynamic, and reciprocal interaction of the three factors that influence individual behaviors and actions. Bandura (1986, 1989) argued that the human mind is an active force in developing individual behaviors and those individual behaviors are largely regulated antecedently through an internal process.

Bandura (1986, 1989) concluded that people’s behaviors are usually based on their values and expectations, which in turn imposes structure on their actions. Bandura (1986, 1989) then advanced two major sets of *expectations* that results from the active forces spawning from the cognitive process that guides human behavior. The first set of expectations deals with *outcome expectations*. Bandura argued that, individuals are more likely to engage in behaviors that they anticipate would result in favorable outcomes and may shy away from those that may seem to have unfavorable consequences (Bandura, 1986). That is, individuals perform behaviors based on the values they place on the potential outcomes. For the second set of expectations, Bandura called it *self-efficacy*, which is the belief about the individual's ability to successfully perform tasks in a specific domain. Bandura (1986, 1989) argued that self-efficacy influences the choices about which behavior the individual may want to embark on, what effort and how much persistence they will be willing to exert on their actions in the face of obstacles.

The SCCT holds that the cognitive-persons' variable (e.g., self-efficacy, outcome expectations, performance interests and goals), the external environmental supports and barriers (e.g., availability of requisite resources and opportunities like money, time, climate, dependence on others), and explicit behaviors (e.g., career or educational decision) interact in a dynamic and reciprocal way via feedback loops that can either enhance or impede the career and educational development processes and mechanisms, such as interests, choice, performance goals, and satisfaction (Navarro, Flores, and Worthington, 2007; Lent et al,. 2013).

The SCCT proposes that individuals will develop interests and make progress at their personally valued goals (performance goals and interest) in those activities that they feel competent and confidence in their ability to accomplish them (self-efficacy) and for which they anticipate receipt of a favorable outcome (outcome expectations) when performing that behavior. Figure 1 shows the SCCT basic model of person, contextual/environment, and experiential (behavior) factors that influences academic and career-related choice behavior.

The SCCT model states that personal inputs and contextual background directly determine students' learning experiences, which in turn is directly associated with their self-efficacy and outcome expectations. These factors together affect students' interests which influence goals and ultimately lead to students' persistence.

Several studies have been generated in support of the utility of the SCCT. Majority of these studies have demonstrated positive association between self-efficiency (academic/math and science), outcome expectations, interest in STEM and STEM persistence. The SCCT forms the appropriate theoretical lens to study STEM persistence and has been applied to a number of STEM related studies on academic performance and persistence (Byars-Winston, Estrada, Howard, Davis, and Zalapa, 2010; Lent, Lopez, Lopez, and Sheu, 2008). Using SCCT, Byars-Winston and colleagues (2010) examined the relationship between social cognitive variables (math/science self-efficacy, math/science outcome expectations) and how students perceived campus climate to STEM interests and commitment to attain a degree in STEM.

Conceptual Framework

The conceptual framework for this study is depicted in Figure 2 as pathways to STEM persistence and degree completion status among seven key variable clusters. In this study, the main focus is on the extent to which STEM persistence and degree completion status is determined by (a) students' self-efficacy beliefs, (b) outcome expectations, and (c) STEM Interest after controlling for background characteristics and contextual supports and barriers? The conceptual model for the present study using the key non-cognitive constructs extracted from the SCCT framework is presented below in Figure 2.

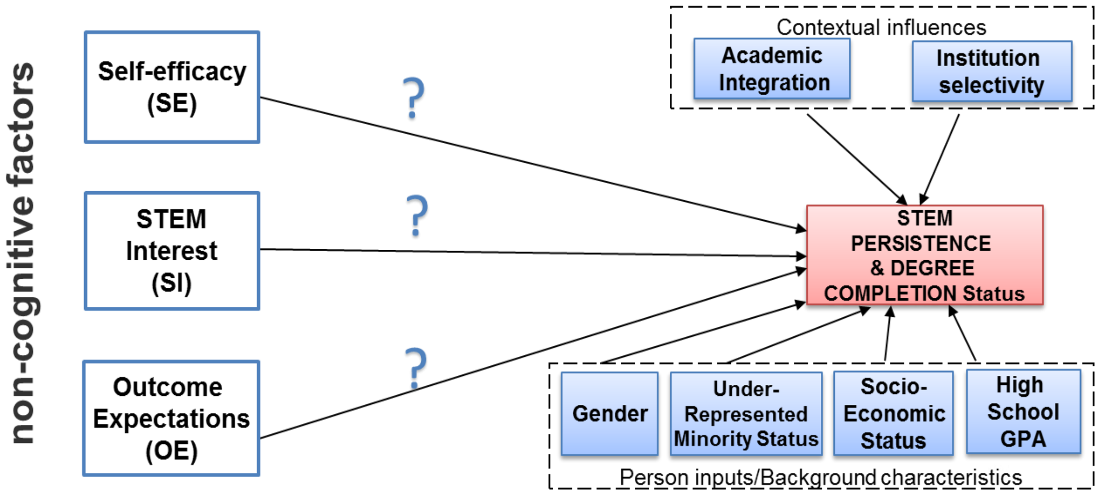

Figure 2: modified STEM persistence and degree completion framework

Review of core variables in the conceptual framework

This section reviews three of the core construct of the SCCT— *Self-efficacy*, *outcome expectations*, and *interests*—which are the main variables of investigation for the present study.

Self-Efficacy

Much research shows that self-efficacy is a key predictor of academic and career choices as well as educational and career development (Lent, Brown, & Hacket, 2000). According to Bandura (1997), self-efficacy is the most important construct underlying persistence. People with higher self-efficacy to complete their educational requirements tend to persevere in the face of difficulties. They also tend to consider a wider range of options that will help them to persist and succeed (Bandura, 1997). Self-efficacy plays a key role in influencing a person's decision making, choices, achievement, and persistence. Self-efficacy gives a person the confidence that they have the ability to exercise control over life outcomes, which propels them with the tenacity to see to it that their desired goals comes to completion. Because individuals with strong self-efficacy tend to persist for a longer period of time, such individuals are more likely to have higher levels of academic achievement and persist in college (Schunk and Pajares, 2002).

Bandura (1997) defined self-efficacy as “people’s judgment of their capabilities to organize and execute courses of action required to attain designated type of performance” (p. 391). Self-Efficacy is usually a psychological concept, since it describes the confidence that an individual may have gathered internally to motivate him or her to think that he or she can successfully execute the necessary actions needed to accomplish all tasks required to achieve a set goal. It usually answers the question “Can I do this?” Bandura (1997) reported that self-efficacy forms the foundation of what people think, how they feel, how they are motivated, and how they select and pursue their choices. It is known that people with high self-efficacy may set high goals for themselves; they may develop strong strategies to implement those goals; and, they may be willing to persist in the face of challenges and occasional setbacks (Bandura, 1997; Pajares 1997). Bandura (1997) identified four main sources of self-efficacy: mastery experiences (experiences from one’s own past performance), vicarious experiences (learning from others such as role models), social persuasion (receiving praise and reassurance from others) and, emotional state (arousal, satisfaction).

Self-efficacy also gives a person the confidence that they have the ability to exercise control over life outcomes, which propels them with the tenacity to see to it that their desired goals comes to completion. Because individuals with self-efficacy tend to persist for a longer period of time, such individuals are more likely to have higher levels of academic achievement and persist in college (Schunk and Pajares, 2002).

A students’ self-efficacy in STEM coursework may be assessed by either measuring their academic self-efficacy (which refers to the confidence they have in their ability to complete academic the requirements in their STEM majors) or could be measured through a course specific self-efficacy which, in the case of STEM, is usually their math self-efficacy or their science-self efficacy (Lent et al., 2005; Schunk and Pajares, 2002).

Several studies among STEM undergraduates have associated positive self-efficacy with increased persistence and academic achievement (cf. Bong and Skaalvik, 2003; Eccles and Wigfield, 2002; Lent, Brown, Schmidt, Brenner, Lyons, & Treistman, 2003; Perez et al., 2014; Wang, 2013). Perez and colleagues (2014) found that self-efficacy played a significant role in predicting students' persistence in STEM. Komanrraju and Nadler (2013) also found that academic self-efficacy is a predictor of academic achievement even after controlling for academic ability. Several researchers have pointed out that, academic self-efficacy beliefs nurture social integration and foster the intention to persist, thus easing the stressful environment of college life (Torres and Solberg, 2001; Bong & Skaalvik, 2003; Linnenbrink & Pintrich, 2003).

Math Self-Efficacy: Since success in STEM coursework are based on a strong math and science foundation, studies have shown that math self-efficacy can be used as a measure of student's self-efficacy in STEM coursework (Bandura, 1997; Britner and Pajares, 2001; Wang 2013). Wang (2013) found that math self-efficacy was an important predictor of continuous STEM enrollment. The author found that students who have high confidence in their ability to succeed in mathematics related or science related classes were more likely to elect to continue and persist in STEM.

Self-Efficacy and other SCCT constructs: The SCCT advance that self-efficacy is expected to directly influence students' interests (i.e., "Do I want to do this?), their goals, as well as students' outcome expectations (i.e., "What will happen if I do this"). However, self-efficacy is influenced directly by individuals' learning experiences. Self-efficacy encourages and promotes interests in STEM related tasks as well as directly and indirectly helps students to take the necessary steps to achieve their desired goals. Tang, Pan, and Newmeger (2008) found that high school students with high self-efficacy were more likely to persist in their STEM major coursework at the postsecondary level than their counterparts with low self-efficacy. In another study, Subotnik, Edominston, and Rayhack (2007) found that students who were exposed to mathematics and science early at the pre-college level had greater levels of self-efficacy and had better opportunity to develop higher interest in STEM disciplines.

Lent, Brown, and Hackett (1996) hypothesized that people who are exposed to a positive learning experiences would be more likely to have higher self-efficacy. Several studies (e.g., Griffin, 2010; Lent, Brown, & Hackett, 1996) have found evidence to support a positive relationship between self-efficacy and students' learning experiences.

Self-Efficacy and Gender: Lent, Brown, Schmidt, Brenner, Lyons, & Treistman (2003) have demonstrated that women are especially sensitive to issues of self-efficacy. Other studies have also documented that, even when women have the same grade and ability as men, majority of women who leave STEM disciplines do so because that have less confidence (self-efficacy) in their abilities compared to those women who persist (Hutchison-Green, Follman, & Bodner, 2008; Taylor & Walton, 2011). Similarly, other studies have shown that women who do persist in STEM fields have lower self-efficacy than their male counterparts (Hutchison, Follman, Sumpter, & Bodner, 2006; Deemer, Thoman, Chase and Smith, 2014). Research suggests that certain specific stereotypes pertaining to women in STEM have negatively influence women's performance and experiences (Schmader, Johns, & Forbes, 2008; Deemer, Thoman, Chase & Smith, 2014).

Self-Efficacy and Race/Ethnicity: Bandura (1997) suggested that people from minority ethnic groups are more likely to have lower self-efficacy due to the inadequate exposure to the main sources of self-efficacy such as positive role models, encouragement, and better learning environments. Britner and Pajares (2006) investigated whether the science motivation beliefs of middle school students were associated with race/ethnicity and also whether self-efficacy beliefs predict science achievement and persistence. They found that White students had stronger self-efficacy than the other racial groups, more especially non-Asian minority ethnic groups.

Self-efficacy beliefs have also been shown to be very sensitive to contextual environmental influences. Chithambo et al., (2014) found that the contextual environment that is perceived by students as being discriminatory against them may decrease minority students' self-efficacy beliefs. Additional evidence from Reynolds and college (2010) suggest that higher levels of on-campus discrimination were associated with low levels of confidence and motivation among minority students in STEM. Lent, Brown, Schmidt, Brenner, Lyons, & Treistman (2003) have demonstrated that women are especially sensitive to issues of self-efficacy.

Outcome Expectations

Outcome expectations belief is another core construct of the SCCT. It refers to individuals' beliefs concerning the anticipated consequences of engaging in a given behavior or performing a given task (Bandura, 1997). The outcome expectations of an individual help determine that person's perception of the consequences of their actions or behavior. Outcome expectations is usually evaluative in nature (i.e., "What will happen if I do this" (Lent and Hackett, 1987, p. 348)). It tells us whether an individual anticipates a positive (good, pleasant) or a negative (bad, unpleasant) results from pursuing a certain course of action.

The SCCT proposed that individuals tend to engage more in activities that they imagine will offer them the most favorable or positive outcomes (Lent et al., 1994). On the other hand, people try to avoid those activities whose outcome they imagine may bring them shame or an undesirable or negative result (Lent et al., 1994). Because outcome expectations beliefs occur prior to the performance of a given behavior, past learning experiences is very crucial when determining what factors influences outcome expectations. Based on past learning experiences, individuals are able to estimate what the consequence of an intended behavior could possibly be if acted upon it (Lent et al., 1994, 1996).

The consequences expected from pursuing certain courses of actions may be categorized in three forms: physical (e.g., monetary rewards, physical pleasure, etc.), social (e.g., power, shame, prestige, social approval, rejection, disapproval, etc.), and self-evaluation (self-satisfaction, emotional reactions e.g. pride, anger, fear, guilt, grief, joy). The sources of information to create one's own outcome expectations may be obtained either by observing other people's behaviors or courses of actions within the environment (e.g., observing how much STEM workers in a particular discipline earn) or could be based on one's own past experiences.

Very few studies have addressed constructs involving outcome expectations and its empirical relationship to the other constructs of the SCCT. Byars-Winston et al., (2010) conducted a path analysis using a sample of 223 undergraduate minority students who were STEM majors. Their results demonstrated that math and science self-efficacy and outcome math and science expectations were associated with minority students persisting as well as completing their STEM degrees. Similarly, Kahn & Nauta (2001) used SCCT to demonstrate that in situations where students have low academic self-efficacy, and their outcome expectations regarding college completion were negative, their performance goals were more likely to be discordant with persisting, and such students were at risk of dropping out of college.

This study hypothesizes that students with high outcome expectations beliefs would be more likely to persist to STEM degree completion than those with low outcome expectations beliefs.

Interests

Students' interests (i.e., "Do I really want to do this?") represent another core construct of the SCCT. Interests refer to the degree to which individuals prefer or favor particular tasks over others (e.g., completing science homework, solving complicated technical problems). Interests promote goal related activities which include active involvement and skills acquisition. By "liking something" (interests) individuals take the next steps to set goals to achieve what they liked. The SCCT hypothesized that interests creates the pathway that guides individuals to follow a particular course of action (choice goals) and then motivates them to undertake the steps necessary to successfully accomplish that goal (choice actions). That is, interests motivate individuals to choose or set goals and take the necessary actions to attain the goal. This study focuses on interests that are potentially related to the STEM major fields.

The process of developing STEM interests is dynamic and continually evolving through the information students receive from their learning experiences and outcomes (Lent, Hackett, and Brown, 1996). Through learning experiences, students develop some expectations about pursuing certain courses of actions and develop a pattern of likes, dislikes, or indifference for STEM courses or STEM related activities (Lent, 2005). Studies show that high school students who are exposed early on to STEM courses and STEM related activities tend to express greater interests in STEM courses (Newton, Torres and Rivero, 2011; Enberg & Woniak, 2013; Lee & Judy, 2011; Wang, 2013).

Given that the development of STEM interest depends on exposure to activities and continuous evaluation of the actual outcomes, it seems reasonable to suggest that being exposed to a small range of STEM-related activities will eventually lead to a lower STEM interests. Similarly, being exposed to a large range of STEM-related activities will lead to a higher level of interests in STEM courses. For example, studies show that the higher the quantity and quality of STEM related courses taken during high school the more likely that students would take higher STEM courses in college and the higher the number of students that persist to STEM degree completion (Enberg and Woniak, 2013; Maltese & Tai, 2011; Wang, 2013; NSF, 2009).

Ainley and Ainley (2011) acknowledged that interests do not develop in isolation, rather interests increase as the feelings of positive self-efficacy and positive outcome expectations also increase. Yet, Bandura (1997) argued that, although both self-efficacy and outcome expectations jointly influence interests, self-efficacy tends to be stronger predictor of interests for most of the time than outcome expectations. Bandura (1986) was of the view that personal efficacy beliefs constitute the key factor of human agency (Pajares, 1996). For instance, just because an individual expects a positive outcome from engaging in a behavior does not necessarily mean that the individual will automatically take the necessary actions to attain the goal.

Summary

The primary goal of the present study is to gain better understanding of non-cognitive characteristics (self-efficacy, outcome expectations, and interest) of students and how it may contribute to the persistence to college degree completion in STEM for students who attended postsecondary institutions in the United States. The goal is to provide more explanation and predictive validity to models used in predicting college persistence. In sum, self-efficacy, outcome expectations, and interests are especially important in predicting persistence in STEM disciplines.

CHAPTER III

RESEARCH METHODOLOGY

This study examined the influence of self-efficacy, outcome expectations, interest, background, contextual and environmental influences on STEM persistence and degree completion. As the literature review chapter indicated, the SCCT framework represents a comprehensive and testable model of student outcomes such as persistence and incorporates a wide array of constructs that have been identified in prior research as having influential impact on student outcomes. In this chapter, I will discuss the research methodology of the study. The following section introduces the sample, measures, study procedure and data analysis strategies. The current study utilized a nationally representative Education Longitudinal Study (ELS) panel data to address the research questions.

Source of data

Data used for this study was drawn from the Educational Longitudinal Study (hereafter referred to as ELS:2002). The ELS:2002 is a nationally representative longitudinal data set collected by the National Center for Education Statistics (NCES). It was sponsored by the U.S. Department of Education. It was also designed to monitor and provide trend data about critical transitions experienced by young adults as they progress from tenth grade through high school, and as they leave high school and progressed through postsecondary institutions and/or as they left school and joined the labor market or the military (Ingels, Pratt, Rogers, Seigal & Stutts, 2014). The benefit of using the ELS:2002 data set, which was a longitudinal survey, was that it allows researchers to follow and collect data on the same cohort of participants over some time period. In such a longitudinal design, the same or mostly similar variables may be collected across different waves allowing researchers to assess students' achievement, persistence, attitudes and experiences over time through a student questionnaire.

The selection of ELS:2002 data for this study

First, the extensive volume of data offered by the ELS:2002 dataset, which include numerous background and students' demographic data, behavioral and attitudinal non-cognitive information, as well as the outcome variable used in this study (STEM degree completion status), made the ELS:2002 dataset very attractive for this study. The ELS survey used data collected on students' academic, social, and educational experiences and outcomes, their personal and academic goals and student's transcripts from secondary to post-secondary level. In addition to information gathered from student respondents, the ELS:2002 study also obtained information from student's parents, teachers, librarians, and high school administrators. The very large volume of data in the ELS:2002 dataset allowed researchers to study many factors that could not easily be captured in a narrower study. Secondly, due to its longitudinal nature, researchers were able to explore the relative significance of various factors affecting students' persistence as well as attrition from STEM fields as they transitioned across different time periods.

Of the high school longitudinal studies available from NCES that may have legitimate application for this study, ELS:2002 data was the most recent study that was complete. Although the High School Longitudinal Study of 2009 (HSLS:2009) was more current, it had not sufficiently been advanced in time (e.g., the third follow-up was yet to be released) for this study. Similarly, prior NCES longitudinal studies such as the National Education Longitudinal Study of 1988 (NELS:88) and High School and Beyond (HS&B) may be complete, but they do not reflect the current trends in education as they capture earlier (1980s and 1990s) educational trends. Unlike the other longitudinal survey conducted by the NCES such as the High School

Longitudinal Study (HSLS:2009) of 2009, the ELS:2002 had more information on the noncognitive variables of interest for this current study. For example, the HSLS:2009, which was the most recent longitudinal survey from NCES, a successor to ELS:2002, do not include many of the noncognitive variables indicators noted in the ELS:2002. Another key advantage of using the ELS:2002 over the most recent, longitudinal, and nationally representative data available, HSLS:2009, was that ELS:2002 provided postsecondary degree completion data for students (which was used as the outcome variable of this study) whereas the current HSLS:2009 did not provide such information. Most of the variables needed for the current study was publicly available in the public-use version of ELS:2002.

Sampling

Base-year data collection for the ELS:2002 started with students in the tenth grade of high school during the spring term of 2002. The data collection was based on a two-stage probability sampling design. First, the ELS:2002 survey was stratified by region of the country and then clustered at the school level. In the first stage, a nationally-representative sample of 1,221 eligible public, private, and Catholic high schools which have 10th grade students were selected from a population of approximately 25,000 high schools, but only 752 agreed to participate in the study (representing 67.8 percent weighted participation rate). Second, instead of taking a simple random sample of students from the combined pool of schools, rather, a probability sample was taken from each school. The ELS:2002 designers believed that, by clustering the sample of students at the school level, students from the same school would have similar attributes when grouped together, compared to grouping students from different schools (Ingels, Pratt, Rogers, Seigal & Stutts, 2014). Thus, in the second stage, approximately 26 students were chosen using an unequal probability of selection from each of the 752-participating schools. To ensure that adequate information about small subgroups of the populations had a better chance of entering the ELS:2002 sample, over-sampling was used in many schools (especially private schools) and for the Asian and Hispanic students (Ingels et al, 2014). The ELS:2002 dataset provided probability weights to compensate for the over-sampling of various subgroups as well as adjustment for nonresponse effects. The weights were provided to ensure that school-level samples (i.e., the clustering of samples of students by schools) will be representative of a national sample. Of a total of 17,590 students who were eligible and selected, 15,360 students completed the ELS:2002 base year student survey (87.3 percent weighted response rate). The above sampling was known as “complex survey sampling” where some individuals in the population had different probabilities of being selected into the sample based on some characteristics they possessed (Natarajan et al., 2008).

The first follow-up was conducted during the spring of 2004. The sample was “freshened” during the first follow-up in 2004 in order to maintain a nationally representative cohort of high school seniors, these were 12th grade population comprising 2004 seniors and 2002 sophomores. Of a total of 16,515 students who were selected, 14,989 students participated the first follow-up student survey (88.7 percent weighted response rate). Data collections for the first follow-up were primarily conducted in school within group sessions. It was also followed by the collection of high school transcripts.

The second follow-up was conducted in the spring of 2006 when the majority of the students in that cohort had graduated and transitioned from high school to postsecondary education, or moved on to the labor market or to the military. Data collection for the second follow-up was conducted primarily through telephone interviews and self-administered Web interviews while supplemented by computer-assisted personal interviews. The third follow-up was conducted in 2012. Additional information about their college academic and social experiences, labor market earnings and satisfaction were collected. It was also followed by the collection of postsecondary education transcript in 2013.

Analytic Sample for this study

Sample definition. Sample members of ELS:2002 respondents were included in the analysis if they:

- Were in the 10th grade in 2002
- Were enrolled in a postsecondary institution (4-year institution) within two years following high school graduation in 2004.
- Had participated in all four waves: BY (2002), F1 (2004), F2 (2006), and F3 (2012).
- Declared their major field of study in 2006 (F2) as STEM.

To obtain the final dataset, this study used the public version of the ELS dataset to identify variables regarding students' responses about their declared major (F2B22) and the major field of study (F2MAJOR2). Only students who declared their major and whose postsecondary major field of study as of 2006 was in STEM fields were included in the analytic sample. To obtain this information, students were asked whether they had declared a major yet at their current postsecondary educational institution and what that major field of study was during the 2006 interview.

To determine the student's major, an item from the second follow-up (F2) for which students reported their major category (major in 2006, 2-digit code) was recoded to create a dichotomous variable, where STEM =1 if student declared STEM major, or STEM=0 otherwise.

The two-digit codes that were recoded as STEM major were: (01) Agriculture/natural resources/related; (05) Biological and Biomedical sciences; (08) Computer/information sciences/support tech; (11) Engineering technologies/technicians; (18) Mathematics and statistics; and, (25) Physical sciences. This selection was consistent with Department of Education's National Center for Education Statistics (NCES) definition of "STEM field" and the Department of Homeland Security's STEM Designated Degree Program list of fields of study considered to be science, technology, engineering or mathematics (STEM) fields of study. This classification was also consistent with NCES report authored by Chen and Weko (2009), who utilized the following major classifications in the determination of STEM degree measure: biological and biomedical sciences; agricultural and natural resources related sciences; physical sciences; computer sciences; engineering; health professions and clinical sciences; mathematics and statistics;   science technologies/technicians, engineering technologies/technicians, precision production, mechanical/repair technologies, and computer/information sciences/support technicians.

Determination of analytic sample size

Of the 16,197 records on students in the in the ELS dataset, 9,706 had participated in all four waves: BY (2002), F1 (2004), F2 (2006), and F3 (2012). Because the current study included focused only on students who attended a four-year postsecondary institution within two years following high school graduation in 2004, the 9,706 observations were reduced to 5,930 records. Of the students who participated in all four waves and were enrolled in four-year institutions, 4,045 (or 68.4%) declared their major field of study in 2006 (F2). Of these students who declared their major in 2006, 834 (21.2%) declared their major field of study as STEM. After using listwise deletion for any remaining missing cases on the independent and dependent variables, a final analytic sample yielded 710 observations. The final data set for this study contained a sample size of 710 participants from the public ELS:2002 dataset who were 10th-grade students in 2002, enrolled in a 4-year postsecondary institution by 2006, followed-up through 2004, 2006, and 2012, and who had declared STEM major in 2006. Women represented only 41.4% percent (n= 294) of participants who have decided to pursue a STEM major compared to 58.6 percent (n = 416) of their male counterparts. According to the 2009 American Community Survey (ACS) of the U.S. Census Bureau, women comprise just 24 percent of STEM workers (U.S. Department of Commerce, Economics and Statistics Administration, 2011). The analytic sample for this study had the following distribution of race/ethnicity of students: 60.6% (n=430) White, 17.5% (n=124) Asian, 10.6% (n=75) African American, 7.6% (n=54) Hispanic, 3.8% (n=27) represent all other ethnic and multi-racial groups.

Measures

This section introduces the measures that were chosen based on the proposed conceptual framework to assessed the primary outcome variable, STEM persistence and completion status, the non-cognitive (independent) variables (self-efficacy, outcome expectations, and interest), and the background, contextual and environmental variables.

Outcome variable

The outcome variable of interest in this study is STEM persistence and degree completion status (SPADCs), as of 2012, which was constructed from survey items in the ELS 2012 (wave F3) dataset. Although all the individuals in the analytic sample were students who had declared a STEM major (or entered a STEM field), not all of them persisted to earn a STEM degree.

Those students who did not earn a STEM degree were classified into two categories. These comprised of those who declared STEM students major but switched to a non-STEM major and ended up earning a *Non-STEM degree* and those who did not attain any degree (*no degree)* at all. Thus, the outcome variable *STEM persistence and degree completion status* of this study classified students into three separate mutually exclusive outcome categories of ***STEM Degree*** (i.e., STEM students who earned at least a Bachelor's degree or higher in STEM field -- coded 3), ***Non-STEM Degree*** (i.e., STEM Students who changed majors and attained at least a Bachelor's degree or higher in a non-STEM degree -- coded 2), or ***No Degree*** (STEM Students who did not complete any degree or credential as of F3 or dropped out -- coded 1). The most desirable outcome category for a STEM student is to obtain a *STEM Degree*.

The noncognitive independent variables

The study included the following three groups of independent variables identified as non-cognitive attributes: self-efficacy, outcome expectations, and STEM interest. Also, several contextual, background and environmental factors were included to assess their influence on STEM persistence and degree completion status.

Self-efficacy

Based on previous research (e.g., Wang, 2013), mathematics self-efficacy was used as a proxy for STEM self-efficacy allowing for the examination of the student's belief about his or her ability to successfully perform some specific math tasks or behaviors. For this study, mathematics self-efficacy was measured when the student was in the tenth grade of high school. This construct was indicated by three questions on the base year survey which asked students to rate their level of agreement with the following statements: “I’m certain I can understand the most difficult material presented in math texts,” “I’m confident I can understand the most complex material presented by my math teacher,” and “I’m certain I can master the skills being taught in my math class.” Each statement asks students to rate themselves on a four-point Likert scale (1= “Almost never”, 4= “Almost Always”).

Outcome Expectations

Outcome expectations operates through anticipation mechanism (that is, the desire students want to achieve). An individual performing any task may anticipate the task consequences to be positive (favorable) or negative (undesirable) (Fouad & Guillen, 2006). Individuals will approach and not avoid a task that they can imagine its overall consequences in a favorable light. Thus, a positive feeling about the outcome of the choice may influence their intention to remain with the choice. As such, outcome expectations are evaluative in nature in that it examines what might motivate a student to undertake a particular task or to persist beyond the confidence they have in their own ability to perform the task (i.e., beyond their self-efficacy). (Shoffner, Newsome, Barrio Minton, & Wachter Morris, 2015).

To measure this latent construct, three questions on the base year survey were used. The questions asked students to rate their level of agreement with the following statements: “I study to get good grade,” “I study to increase my job opportunities,” and “I study to ensure that my future will be financially secure.” Each statement asks students to rate themselves on a four-point Likert scale (1=“Almost never”, 4=“Almost Always”).

STEM Interest

STEM Interest measures whether a student had an intent to pursue a major in STEM fields upon entry into a postsecondary institution. STEM Interest captures the student's level of curiosity in stem-related activities or issues that excites him or her and bring about enthusiasm for engaging in STEM related activities. Students with high interest in pursuing a major in a STEM field (STEM interest) most likely have high intent to participate in STEM activities and may have a strong belief that taking science and/or math courses is a sensible, useful and worthwhile endeavor. For this study, interest was operationalized by determining whether the most likely postsecondary field of study they considered when they began their postsecondary education was in the STEM disciplines. To measure this binary categorical variable, one question on the second follow up survey were used. The question asked students about the most likely major they will pursue when they started attending their first postsecondary institution. They had to choose one response from a list of sixteen majors (see Appendix E). A student's response to this question was recoded as *STEM Interest* = 1 when the field of study respondent would most likely pursue at the first postsecondary institution was in STEM field and *STEM Interest* = 0 otherwise.

Background, Contextual and environmental Variables

Not only do students have different background, contextual and environmental characteristics (demands within their environment which permits, provides, or hinders their progress), but also, their perceptions about their background, contextual and environmental characteristics differ. By measuring and considering these perceptions, it might guide researchers to better understand the environmental cues that these perceptions have on student persistence and degree completion in STEM fields. The contextual and environmental characteristics in the SCCT framework generally refers to important independent variables which have been proposed to have either a proximal (or immediate) or distal effect on the dependent variable (STEM persistence and degree completion status) for which students have little or no control over them.

Guided by our SCCT framework, I selected six background, contextual and environmental variables as having a distal or proximal influence on the noncognitive variables (self-efficacy, outcome expectations, and STEM interest) and the outcome variable (STEM persistence and degree completion status). These include four background variables common to most analysis (students' gender, ethnicity, socio-economic status (SES), and high-school grade point average (HSGPA)) —referred to as block 1 in this study— and two contextual and environmental variables (academic integration, and institutional selectivity) — referred to as block 2 in this study. Students' academic integration, according to Tinto (1975, 1993), refers to the variety of academic experiences and relationships that promoted a feeling of personally belonging to the academic milieu of the campus environment. Students' academic integration was measured using their response to the question "Talk with faculty about academic matters outside of class." Institutional selectivity constitutes institutional quality and the excellence of the undergraduate education that a student receives from his or her postsecondary institution. It discovers if students at more selective institutions have greater advantage in attaining a STEM degree than those in less selective institutions. Given that these six background, contextual and environmental variables have important confounding influences on both the noncognitive variables and the outcome variable, they were all treated as covariates. They were controlled for in all the analysis.

Statistical Data Analysis

The data analysis for this research proceeded in several steps, based on the research questions. For the first and second research questions (which ask: "Are there any differences in self-efficacy by STEM persistence and degree completion status?" and "Are there any differences in outcome expectations by STEM persistence and degree completion status?" respectively), I used one-way analysis of variance (ANOVA) model to examine if there were any distinct differences in *self-efficacy* and *outcome expectations* scores among the three categories of STEM persistence and college degree completion status (completed STEM degree, completed non-STEM degree, No degree). A one-way ANOVA was appropriate given that both the *self-efficacy* and *outcome expectations* scores were measured on the continuous scale whereas the *STEM persistence and degree completion status* (SPADCs) was a categorical variable with more than two response categories. Where the ANOVA results was significant, to determine exactly which means differed significantly, I conducted a post hoc pairwise comparison analysis using Fisher's least significant difference (LSD) technique.

For the third research question (which asked: "Is there a relationship between STEM interest and STEM persistence and degree completion status?"), due to the categorical nature of the noncognitive variable *STEM Interest*, a Chi-square statistical testing technique was employed to test for differences.

For the remaining two research questions (four and five) — "To what extent, if any, do students' demographic/background characteristics (e.g., gender, ethnicity, socio-economic status, and high school GPA) and students' contextual and environmental characteristics (e.g., academic integration, and institutional selectivity) affect their STEM persistence and degree completion status?” and “Controlling for demographic and background characteristics and students’ contextual and environmental characteristics, to what extent do individuals’ non-cognitive attributes (i.e., self-efficacy, outcome expectations, and STEM interest) contribute to STEM persistence and degree completion status?” — was analyzed using a hierarchical multinomial logistic regression (MLR) techniques. Multinomial logistic regression model, which is generally used to handle outcome variable that has more than two nominal or unordered categories (e.g. Menard, 2002; Tabachnick et al., 2001; Harrell, 2001; Hosmer & Lemeshow, 2000) was used to model the relationship between all the predictor variables in the study and the dependent variable (STEM persistence and degree completion status) of this study. The outcome variable consists of three non-overlapping mutually exclusive nominal categories: *STEM Degree Earners*, *Non-STEM Degree Earner*, and *No Degree Earner.*

Multinomial Logistic Regression (MLR)

When dealing with categorical dependent variable *Y* that takes on more than two nominal response categories (or a discrete set of values reflecting *c* separate categories, where c is greater than 2), multinomial logistic regression is a more superior statistical strategy to analyze such data than the regular multiple regression approach. The multinomial logistic regression model can also be used to predict the probabilities of the different *c* possible categories of the dependent variable for any given set of explanatory variables.

To write the equation of the multinomial regression model, the first step is to suppose that the response variable under consideration has *c* categories (with j = 1, 2, . . .c). For this current study, *c* = 3 and the categories of the outcome variable are identified as “No degree” (j =1), “Non-STEM Degree” (j = 2) and “STEM Degree” (j =3). For data comprising the response variable Y with c nominal categories and *k* explanatory variables (denoted by X_{1i}, X_{2i}, $X_{3i}, \ldots, X_{ki}$, where *i* denote each student) which may be categorical, interval or ratio scale variables, the ***multinomial logistic regression*** equation (MLR) will be given by the following equation:

$$log\left(\frac{Prob(Y=j)}{Prob(Y=j')}\right) = \alpha_j + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} \qquad \text{Equation (1)}$$

where j' is the reference category of Y.

The expression to the left of the above equation (1) is called a *logit*. It refers to the log of the odds that an event occurs. Each logit has its own α_j intercept term. The effect of each independent variable (the $\beta_p's$) are different for the different logit functions. Because the response variable of this model has three (*c* = 3) categories, two (*c*-1) logits will be defined for this analysis as *j* takes values from 1=No Degree to 3=STEM Degree. Since X_i had a length of p (p independent variables), there will be $(c-1)\times p$ parameters to be estimated by each logit equation. The equations of the two logit models for the present study are as follows:

$$\begin{aligned} log\left(\frac{Prob(Y = \text{STEM Degree })}{Prob(Y = \text{No Degree})}\right) = \; & \alpha_j + \beta_{1p} Gender_p + \beta_{2p} Race_p \\ & + \beta_{3p} SES_p + \beta_{4p} HSGPA_p \\ & + \beta_{5p} Integration_p + \beta_{6p} Selectivity_p \\ & + \beta_7 \boldsymbol{SE} + \beta_8 \boldsymbol{OE} + \beta_9 \boldsymbol{SI} \end{aligned}$$

Equation (2)

$$\begin{aligned} log\left(\frac{Prob(Y = Non \text{ STEM Degree })}{Prob(Y = \text{No Degree})}\right) = \; & \alpha_j + \beta_{1p} Gender_p + \beta_{2p} Race_p \\ & + \beta_{3p} SES_p + \beta_{4p} HSGPA_p \\ & + \beta_{5p} Integration_p + \beta_{6p} Selectivity_p \\ & + \beta_7 \boldsymbol{SE} + \beta_8 \boldsymbol{OE} + \beta_9 \boldsymbol{SI} \end{aligned}$$

Equation (3)

Analyzing the intercepts and the parameter estimates of the multinomial logistic regression model will help us to understand better the relationship between the dependent variable and the independent variables. As such, the maximum-likelihood method was used to estimate the parameters of the model (Bishop et al. 1975).

The significance of each independent variable was tested globally while controlling the effect of the other independent variables in the model. In addition, several goodness-of-fit tests such as likelihood ratio, Pearson, deviance, and Hosmer-Lemeshow test was carried out. A high probability values for Pearson and deviance statistic will indicate that the model fit the data reasonably well. An insignificant Hosmer-Lemeshow statistic is an indication that the model fit well to the data.

The results of the multinomial logistic regression model was interpreted in terms of the odds ratios (OR = exp(β_j)). The odds ratio is obtained by exponentiation of the value of the coefficient associated with the independent variable. The OR transforms the values of the coefficients to their original scale making it easier to interpret the actual effects of the variables. An OR greater than 1 (which corresponds to a positive estimate of the coefficients β_j) is an indication of a positive effect on the dependent variable (e.g., favors *STEM Degree* completion compared to *No Degree*), while an OR value less than 1 (which corresponds to a negative estimate of the coefficients β_j) is an indication of a negative effect on the dependent variable. The significance of each of the independent variables was examined using the Wald's Test and the associated p-value. If the result is significant, the OR value was analyzed (Tabachnick & Fidell, 2007).

Weights

In the ELS:2002 dataset, different sampling weights have been provided by the designers to account for the complex sampling scheme used in their data collection. Since the respondents in the ELS dataset had unequal probabilities of being included in the survey, the weighting information provided by ELS can be used to obtain to appropriate unbiased estimates of the population parameters of interest. Without applying the appropriate weights, biased estimates of parameters of interest will occur, and this can yield misleading results. Thus, weighting must be used in the statistical analysis of complex sampling designs before the results may be generalized to the entire population. The use of sampling weights also allows for correction to be made in the standard errors, which in turn, helps improve the reliability and accuracy of significant of estimate.

Due to the design of the current study, the appropriate sampling weight panel (F3BYPNLWT), which accommodates the sample members who participated in all four waves of the survey, was used. This weight, which was attached to each unit, was normalized to account for the current sample size. To achieve this, I first calculated the average of population response weight panel variable (F3BYPNLWT) in the analytical sample and then divided each student's panel weight by this average. All statistical analysis performed was based on the data weighted by the normalized weight.

Missing Values

Irrespective of how carefully the researchers of the ELS designed the survey, missing value (or data) problems usually exist and it is a common occurrence in longitudinal study. Missing values impairs the validity of a study assumptions and raises concerns about the internal validity and power of the study unless appropriately addressed. If the internal validity is compromised, researchers might not be able to generalize the results of a study to the population. If missing values are not addressed with the appropriate method, it will result in losing information as well as producing biased estimates.

This study first analyzed the extent to which missing values occurred in the data. First, listwise deletion missing data technique was used to remove all observations for with no information was available on the indicator variables of the independent variables. The outcome variable, STEM Persistence did not have any missing values. Although listwise deletion has been demonstrated to be inferior to other statistical techniques of dealing with missing values (e.g., full information maximum likelihood or multiple imputation), the use of these techniques would have implied imputing data for about 14% of the respondents (See Appendix F for demographic breakdown of missing values). Secondly, listwise deletion still left this present study with sufficient number of respondents (n = 710) to carry out the study analysis.

Limitations

Since this study was built on the use of secondary data (the ELS dataset), it has an inherent limitation of relying mostly on proxy measurement of the SCCT's key constructs, which may not necessarily capture the non-cognitive scale measures originally developed for the theoretical model. For the most part, research projects that used significant portion of the SCCT framework as the guiding model used survey instrument specifically designed for evaluating the SCCT framework (Navarro et al., 2006, Lent et al. 2013). Although all three non-cognitive constructs used in this study utilized the SCCT's key constructs, this research is limited in that it is restricted to the questions and measures used by the ELS team which was not necessarily designed with the SCCT as its focus.

Secondly, the record number of students who declared a major in STEM were only a small percentage of the ELS dataset. Therefore, this severely limited the number of cases available for the analysis of the data. By using the ELS dataset, the sample actually represented the 2002 cohort of 10th grader who declared STEM major by 2006 and participated in the third wave of ELS. As such, the result will be reflective of this group of students, not STEM students in college in general. Other national databases which focuses on cohorts of postsecondary students over time such as the Beginning Postsecondary Students Longitudinal Study (BPS), may provide a more comprehensive representation of the population under consideration. Additionally, since the non-cognitive variables were measured at the high school level, the passage of time may certainly have changed how students conceptualized and operationalized these non-cognitive concepts.

Summary

This chapter provided a description of the dataset used in the study (the ELS:2002-2012), the sample selected for the study and the criteria used in selecting the analytical sample. The methodology to be used in analyzing the analytical sample were also outlined in details along with some key limitations of the study. The chapters that follows will present the results obtained through the use of the methodologies discussed this study and provide a discussion chapter for the main findings together with the implications and suggestions for future research and policy analysis.

CHAPTER IV

RESULTS

The purpose of this study was to examine the extent to which non-cognitive factors (i.e., self-efficacy, outcome expectations, and STEM interest) contribute to undergraduate students' persistence and college degree completion in STEM with particular attention to students enrolled in 4-year colleges and universities in the United States. As described in Chapter three, the analytical sample for this study was drawn from the Educational Longitudinal Study (ELS:2002-2012) dataset. The final sample used for analyses represents the 2002 cohort of 10th graders who declared STEM major by 2006 and participated in the third wave of ELS in 2012. Thus, the result will be reflective of this group of students, not all STEM students in college in general.

In this chapter, the statistical results of the analyses will be presented. I will first discuss the analysis with the descriptive statistics and summary of the sample demographics and their distribution across the three categories of the outcome variable. Next, I will present inferential statistics (ANOVA, Chi-square, and Multinomial Logistic Regression) to examine the relationship between the non-cognitive factors (i.e., self-efficacy, outcome expectations, and STEM interest) and the outcome variable of STEM persistence and degree completion.

In this study, I explored the following research questions:

1. Are there any differences in self-efficacy by STEM persistence and degree completion status?
2. Are there any differences in outcome expectations by STEM persistence and degree completion status?
3. Is there a relationship between STEM interest and STEM persistence and degree completion status?

4. To what extent, if any, do students' demographic/background characteristics (e.g., gender, ethnicity, socio-economic status, and high school GPA) and students' contextual and environmental characteristics (e.g., academic integration, and institutional selectivity) affect their STEM persistence and degree completion status?
5. Controlling for demographic and background characteristics and students' contextual and environmental characteristics, to what extent do individuals' non-cognitive attributes (i.e., self-efficacy, outcome expectations, and STEM interest) contribute to STEM persistence and degree completion status?

Descriptive Statistics

Descriptive Statistics of the Outcome Variable

Table 1 below summarizes the descriptive statistics of the outcome variable, STEM persistence and college degree completion status (SPADCs), which consists of three sub-groups: (1) STEM Degree Earners (i.e., STEM students who earned at least a Bachelor's degree or higher in STEM field), (2) Non-STEM Degree Earners (i.e., STEM students who changed their STEM majors and attained at least a Bachelor's degree or higher in a non-STEM degree), and (3) No Degree Earners (STEM students who attained no degree or credential or dropped out).

Table 1. *Descriptive Statistics of STEM persistence and college degree completion status (N=710).*

Variable	**Number**	**Percentage**
STEM Degree	371	52.3%
Non-STEM Degree	168	23.7%
No Degree	171	24.1%

As noted in Table 1, of the 710 participants in the analytical sample (all of them declaring an initial intention to major in STEM fields), 371 completed a degree in STEM field by 2012 (STEM Degree earners), yielding a completion rate of slightly over half of the study sample (52.3%). Of the remaining 339 participants, 168 (23.7%) switched from STEM major to a non-STEM field and completed a degree in a non-STEM field (non-STEM Degree earners), while the other 171 (24.1%) did not complete any degree or credential at all (No Degree earners).

Descriptive Statistics of the Categorical Independent Variables

Table 2 summarizes the descriptive statistics of the categorical independent variables in the study sample. These variables include gender, race/ethnicity, underrepresented minority status, socioeconomic status, GPA for 9th – 12th grade, institutional selectivity, academic integration, and STEM interest (a non-cognitive variable). Male participants represent more than half (58.6%) of the STEM degree seeking students in the analytical sample compared with 41.4% of female participants. The socioeconomic status (SES) of participants seems to be unevenly distributed across the different socioeconomic groups. Participants from the high socioeconomic quartile represent slightly over half (51.7%) of the study sample, while participants from the low socioeconomic quartile represent only 8.9% of the sample. Participants from the middle socioeconomic quartile 39.4% of the sample.

White students represent 60.6% of the analytical sample, followed by 17.5% of Asian Americans, 10.5% of African Americans, 7.6% of Hispanics and 3.8% of all other races and multi-racial groups. Although the ELS:2002 dataset divides race and ethnicity variable into five categories, a decision was made to reduce this number to two major categories: underrepresented minorities (URMs), comprising African American, Hispanics, Native Americans and all other races and multi-racial groups, and non-underrepresented minorities (non-URMs), comprising whites and Asians. The reason for this decision was based on the need for adequate numbers within the cells so as to generate satisfactory statistical power.

Table 2. *Descriptive Statistics of the Independent Categorical Variables (N=710).*

Variable	**Number**	**Percentages**
Individuals' Characteristics		
Gender		
Male	416	58.6%
Female	294	41.4%
Race/Ethnicity		
African American	75	10.5%
Hispanic	54	7.6%
Asian	124	17.5%
White	430	60.6%
Other Races	27	3.8%
Underrepresented Minority Status		
Underrepresented Minority*	156	22.0%
Non-Underrepresented Minority	554	78.0%
Socioeconomic Status		
High SES	367	51.5%
Mid SES	280	40.2%
Low SES	63	8.3%
GPA for 9th – 12th grade		
High GPA (3.51 – 4.00)	352	47.7%
Moderate GPA (2.51 – 3.50)	276	40.3%
Low GPA (0.00 – 2.50)	82	12.0%
STEM Interest (non-cognitive variable)		
Interested in STEM	434	61.1%
Not interested in STEM	276	38.9%
Institutional Selectivity^		
High Selectivity	388	54.6%
Moderate – Low Selectivity	322	45.4%
Academic Integration		
Often	203	28.6%
Sometimes	419	59.0%
Never	88	12.4%

*Underrepresented Minority consist of African Americans, Hispanics, and all other racial minority groups.
^ For explanation on how this variable was created please see Appendix A.

Majority (78%) of the study sample were identified as non-underrepresented minorities (non-URMs), while only 22% of the participants were classified as underrepresented minorities (URM).

Fifty-five percent (55%) of the sample participants received their education at a highly selective institution compared with 45% who had their education at a moderate to low selective institutions. Moreover, it is worth noting that nearly half (49.6%) of the sample participants graduated from high school with high GPA (3.51-4.0), compared with 11.5% who graduated from high school with low GPA (.00-2.50). Similarly, about thirty-nine percent (39%) of the participants graduated from high school with a moderate GPA (2.51-3.50). As shown in Table 2, although all the participants in the study sample were STEM degree seeking students, 61.1% stated that they had interest in STEM fields before they enrolled in their postsecondary institutions compared with 38.9% who had no interest in STEM fields at all.

Cross-Tabulation of Independent Categorical Variables

The cross-tabulation analysis was carried to compare the characteristics of the background, contextual and environmental variables (all of which are independent categorical variables) across the outcome variable. Table 3 below shows the distribution of the independent categorical variables by *STEM persistence and degree completion* status. Among the male participants, 59.1% attained a *STEM Degree*, 18.2% attained *a non-STEM Degree*, and the remaining 22.8% had *no degree* or any credentials. Similarly, among the female students, 42.5% attained a *STEM Degree*, 31.6% attained a *non-STEM Degree* and the remaining 25.9% had *no degree* or any credentials. For the categorical variable *gender* (in Table 3), a single factor Pearson's chi-square (χ^2) test was applied to the crosstabs procedure to determine whether a correlation exists between the gender and outcome variable of STEM persistence and degree completion status.

Table 3. *Descriptive Statistics of the Independent Categorical Variables by STEM persistence and college degree completion status*

Variable	***Completed No Degree by 2012***	***Completed Non-STEM Degree by 2012***	***Completed STEM Degree by 2012***	***Chi-square test of significance***
Individuals' Characteristics	Number (%)	Number (%)	Number (%)	χ^2
Gender				23.226***
Female	76 (25.9%)	93 (31.6%)	125 (42.5%)	
Male	95 (22.8%)	75 (18.2%)	246 (59.1%)	
Underrepresented Minority Status				14.273**
Underrepresented Minority	55 (35.3%)	35 (22.4%)	66 (42.3%)	
Non-Underrepresented Minority	116 (20.9%)	133 (24.0%)	305 (55.1%)	
Socioeconomic Status				6.13
High SES	82 (22.3%)	91 (24.8%)	194 (52.9%)	
Mid SES	66 (23.6%)	65 (23.2%)	149 (53.2%)	
Low SES	23 (36.5%)	12 (19.0%)	28 (44.4%)	
GPA for 9th – 12th grade				47.70**
High GPA (3.51 – 4.00)	48 (13.6%)	95 (27.0%)	209 (59.4%)	
Moderate GPA (2.51–3.50)	87 (31.5%)	56 (20.3%)	133 (48.2%)	
Low GPA (0.00 – 2.50)	36 (43.9%)	17 (20.7%)	29 (35.4%)	
Institutional Selectivity				28.657***
High Selectivity	64 (16.5%)	94 (24.2%)	230 (59.3%)	
Moderate – Low	107 (33.2%)	74 (23.0%)	141 (43.8%)	
Academic Integration				9.628*
Often	42 (20.7%)	59 (29.1%)	102 (50.2%)	
Sometimes	100 (23.9%)	96 (22.9%)	223 (53.2%)	
Never	29 (33.0%)	13 (14.8%)	46 (52.3%)	

Significant variables are presented with asterisks +p<.10, *p<.05, **p<.01, ***p<.001
URMs represent Underrepresented Minority status
SES represents Socioeconomic Status

The χ^2 (df = 2) test statistic for gender was 23.226 ($p < .001$), and as the P value is lower than 0.05 it can be concluded that there are significant differences in the *non-STEM degree* and *STEM degree* earned between male and female students.

Of the 156 underrepresented minorities (URM) participants whose initial intention was to major in STEM fields, only 42.3% completed a degree in STEM field by 2012, whereas more than half (55.1%) of the non-underrepresented minorities (non-URM) participants completed a degree in a STEM field. For the categorical variable *underrepresented minority status*, a single factor Pearson's chi-square (χ^2) test was applied to the crosstabs procedure to determine whether a correlation exists between underrepresented minority status and STEM persistence and degree completion status. The χ^2 (df = 2) test statistic was 14.273 ($p < .001$), and as the P value is lower than 0.05 it can be concluded that student's minority status is related to STEM persistence and degree completion status. Non-underrepresented minorities are more likely to complete their degree in STEM fields than their underrepresented minorities counterparts. A typical STEM degree seeking student who completed a degree in a STEM field tended to be a non-underrepresented minority (non-URM) student whereas a typical STEM degree seeking student who did not complete any degree or credential at all tended to be an underrepresented minority (URM) student.

For the variable *high school GPA*, a single factor Pearson's chi-square (χ^2) test was applied to the crosstabs procedure to determine whether a correlation exists between underrepresented minority status and STEM persistence and completion status. The χ^2 (df = 6) test statistic was 47.70 ($p < .001$), and as the P value is lower than 0.05 it can be concluded that high school GPA is related to STEM persistence and completion status. Students with high school GPA above 3.5 are more likely to complete their degree in STEM fields than those with high school GPA below 2.0. Another categorical variable that showed significant ($p < .05$) association with the STEM persistence and degree completion (outcome variable) was *academic integration* (χ^2 (6) = 9.628, p=.047). The socioeconomic status variable was not significant at .05 level (χ^2 (6) = 6.13, p=.190). Finally, the *institutional selectivity* categorical variable that showed significant ($p < .001$) association with the STEM persistence and degree completion (outcome variable) was *Academic Integration* (χ^2 (2) = 28.657, p<.001).

Descriptive Statistics of the Self-Efficacy and Outcome Expectations variables

Table 4 summarizes descriptive statistics for non-cognitive independent continuous variables (self-efficacy and outcome expectations scores) among three STEM persistence and college degree completion status groups (completed STEM degree, completed non-STEM degree, No degree). These variables are self-efficacy and outcome expectations. Table 4 shows that the self-efficacy (SE) measurement for all participants in the sample has a mean value of 3.06 with a standard deviation of 0.797. The outcome expectations (OE) measurement in the total sample has a mean value of 3.01 with a standard deviation of 0.818.

Table 4. *Descriptive Statistics of the Independent Continuous Variables*

Variable	Mean	SD	Min	Max
Noncognitive variables				
Self-Efficacy (SE)	3.0577	0.79669	1	4
Outcome Expectations	3.0164	0.81834	1	4

Analysis of Research Questions 1 and 2

Question 1: Are there any differences in self-efficacy by STEM persistence and degree completion status?

Question 2: Are there any differences in outcome expectations by STEM persistence and degree completion status?

To answer research questions 1 and 2, I used a one-way ANOVA to examine if there are there any distinct differences in self-efficacy and outcome expectations scores among the three categories of STEM persistence and college degree completion status (completed STEM degree, completed non-STEM degree, No degree). Before conducting the ANOVA analysis, I evaluated the analytical sample to verify whether all major assumptions of ANOVA (i.e., independent observations, normally distributed populations, and homogeneity of variance) were satisfied. The sample design of the ELS study ensures that the observations are independent. That is, how one student responded to an item on the survey did not in any way influence how another student responded to the same item on the survey. To detect violation of normality, assumption, skewness and kurtosis statistics were calculated. The skewness value were -.462 and -.471 and the kurtosis value were -.750 and -.890 for the self-efficacy and outcome expectations scores respectively. These values are within the normal range expected of chance fluctuations which indicates that the normality assumptions was satisfied (Gall, et al., 2007). For homogeneity of variance, the Levene's test of variance was conducted. The results of this analysis revealed that there was no statistically significant differences in the variance matrices of the self-efficacy and outcome expectations scores across three STEM degree completion status groups ($F(2, 707) = 2.264$, $p = .081$ for self-efficacy and $F(2, 707) = 2.520$, $p = .105$ for outcome expectations). This means that, on average, self-efficacy and outcome expectations scores are homogeneous across the three persistence and degree completion status groups (Gall et al., 2007). Therefore, the assumption of homogeneity of variance across the groups is not violated. Since all major assumptions of ANOVA were satisfied, I used the F-test to determine whether there are significant differences between the three degree-completion status groups of students with respect to their scores on the self-efficacy and outcome expectations respectively. The results were reported by the three STEM persistence and completion status groups and followed by post hoc multiple comparison when appropriate.

I conducted a one-way ANOVA with the three STEM persistence and college degree completion status groups (completed STEM degree, completed non-STEM degree, no degree completed) as the independent variable and the two continuous noncognitive variables (self-efficacy and outcome expectations) scores as the dependent variables. Table 5 below presents the results of the ANOVA of STEM persistence and degree completion status by continuous noncognitive variables (self-efficacy and outcome expectations).

Table 5. *ANOVA of STEM persistence and degree completion status by continuous noncognitive variables (self-efficacy and outcome expectations)*

Variable	Source	*SS*	*df*	*MS*	*F*	Sig.
Self-Efficacy	Between Groups	15.213	2	7.606	11.98	.000
	Within Groups	447.920	706	.634		
	Total	463.132	708			
Outcome	Between Groups	16.720	2	8.360	12.20	.000
	Within Groups	483.575	706	.685		
	Total	500.295	708			

Based on the results in Table 5 presented above, there is a significant difference between students who completed STEM degree, those who completed a non-STEM degree, and those who did not complete any degree at all on the noncognitive variable *self-efficacy* at the p<.005 level, (F(2, 708) = 11.989, p = .000) and on *outcome expectations* (F(2, 708) = 12.360, p = .000). This indicates that the continuous non-cognitive factors of self-efficacy and outcome expectations were significantly different for the three groups of STEM degree seeking students who completed STEM degree, those who completed non-STEM degree, and those who did not complete any degree at all.

Multiple Pairwise Comparison of Self-Efficacy mean scores

To determine exactly which means differed significantly, a post hoc pairwise comparison analysis using Fisher's least significant difference (LSD) technique was conducted. I first considered the multiple comparison of *self-efficacy* as presented in Table 6.

Table 6. Multiple Pairwise Comparison of Self-Efficacy

Comparisons	Mean Difference	Std. Error	95% CI Lower Bound	95% CI Upper Bound
No Degree vs. non-STEM Degree	-0.24*	0.09	-0.41	-0.07
No Degree vs. STEM Degree	-0.36*	0.07	-0.51	-0.22
non-STEM Degree vs. STEM Degree	-0.12	0.07	-0.27	0.02

* $p < 0.05$

Results of the multiple comparison for the non-cognitive variable self-efficacy showed a statistically significant pairwise difference between the mean self-efficacy levels of students who had *no Degree* and students who switched and completed a *non-STEM Degree* (Mean Difference = -.238, p =.005). Similarly, the results indicate statistical significant difference between the mean self-efficacy levels between students who had no Degree and students who completed a

STEM Degree (Mean Difference = -.361, p = .000). In addition, the results indicate no statistical significant difference between the mean self-efficacy levels of students who had non-STEM Degree and students who completed a STEM Degree (Mean Difference = -.122, p = .096).

Multiple Comparison of Outcome Expectations mean scores

The multiple comparison of *outcome expectations* is presented in Table 7.

Table 7. Multiple Pairwise Comparison of Outcome Expectations

Comparisons	Mean Difference	Std. Error	95% CI Lower Bound	95% CI Upper Bound
No Degree vs. non-STEM Degree	-0.43*	0.09	-0.61	-0.26
No Degree vs. STEM Degree	-0.27*	0.08	-0.42	-0.12
non-STEM Degree vs. STEM Degree	-0.16*	0.08	-0.31	-0.01

* $p < 0.05$

Results of the multiple pairwise comparison for the continuous non-cognitive variable *outcome expectations* indicate a statistically significant pairwise difference between the mean *outcome expectations* scores of students who had *no Degree* and students who completed a *Non-STEM Degree* (Mean Difference = -.433, p =.000). Similarly, the results indicate statistical significant pairwise difference between the mean *outcome expectations* scores between students who had *no Degree* and students who completed a *STEM Degree* (Mean Difference = -.270, p = .000). In addition, the results indicate statistical significant pairwise difference between the mean *outcome expectations* scores of students who had *non-STEM Degree* and students who completed a *STEM Degree* (Mean Difference = -.163, p = .033).

Descriptive statistics for the self-efficacy and outcome expectations scores

Table 8 shows the descriptive statistics for the self-efficacy and outcome expectations scores. Comparing the *self-efficacy* scores of students among three STEM persistence and college degree completion status subgroups, students whose degree completion status was *No Degree* earner generally had lower *self-efficacy* compared to *non-STEM Degree* and *STEM Degree* earners.

Table 8. *Descriptive statistics for the self-efficacy and outcome expectations scores*

Dependent Variable	Grouping factor	Mean	Std. Deviation
SELF-EFFICACY	No Degree	2.8567	0.82289
	Non-STEM Degree	3.0446	0.79920
	STEM Degree	3.1563	0.76703
OUTCOME EXPECTATIONS	No Degree	2.7992	0.82246
	Non-STEM Degree	3.1528	0.82044
	STEM Degree	3.0548	0.79808

Table 8 shows the descriptive statistics for the self-efficacy and outcome expectations scores. Comparing the *self-efficacy* scores among three STEM persistence and college degree completion status groups, students whose degree completion status were *No Degree* generally had lower *self-efficacy* beliefs compared to *non-STEM Degree* and *STEM Degree* earners. The mean *self-efficacy* score for the *non-STEM degree* earners (M=3.045, SD=.799) was slightly lower than the mean for the *STEM degree* earners (M=3.156, SD=.767). Similarly, the mean *self-efficacy* score for the *No degree* earners (M=2.866, SD=.823) was slightly lower than the mean for the *non-STEM degree* earners (M=3.044, SD=.823). In addition, the mean scores of the *outcome expectations* shows that students who did not complete any degree (*No Degree*) generally had lower *outcome expectations* compared to *non-STEM Degree* and *STEM Degree* status students. The mean *outcome expectations* score for the *Non-STEM degree* earners (M=3.153, SD=.820) was slightly higher than the mean for the *STEM degree* earners (M=3.055, SD=.798). On the other hand, the mean outcome expectations score for students who did not complete any degree (*No Degree*) earners (M=2.799, SD=.822) was lower than the mean for both the *non-STEM degree* students and for the *STEM degree* earners.

Analysis of Research Question 3

Question 3: Is there a relationship between STEM interest and STEM persistence and degree completion status?

Due to the categorical nature of the noncognitive variable of STEM Interest, the analysis was first conducted using a cross-tabulation procedure followed by a chi-square test of independence. Table 9 below shows the distribution of STEM persistence and completion status by STEM interest. Of the participants interested in STEM, 59.2% attained a STEM Degree, 17.2% attained a non-STEM Degree, and the remaining 23.7% had no degree or any credentials. Of the participants who were not interested in STEM, 41.3% attained a STEM Degree, 34.1% attained a non-STEM Degree, and the remaining 24.6% had no degree or any credentials. Participants who were interested in STEM are more likely to complete their degree in STEM fields than their counterparts who were not interested in STEM.

Again, Table 9 shows the distribution of STEM persistence and completion status by STEM Interest.

Table 9. Distribution of STEM persistence and completion status by STEM Interest

STEM Interest	***No Degree by 2012***	***Completed Non-STEM Degree by 2012***	***Completed STEM Degree by 2012***
	Number (%)	Number (%)	Number (%)
Not Interested in STEM	68 (24.6%)	94 (34.1%)	114 (41.3%)
Interested in STEM	103 (23.7%)	74 (17.1%)	257 (59.2%)
Total	171 (24.1%)	169 (23.8%)	371 (52.2%)

Of those students who were not interested in STEM, 24.6% did not earn any degree, 34.1% earned a college degree in a non-STEM field and 41.3% earned a STEM degree. Comparing the participants not interested in STEM (24.6%) to those interested (23.7%) within the No Degree outcome category, it can be observed that the percentages seem to be closer to each other. The proportion of participants not interested in STEM compared to those interested in STEM does not seem to differ greatly from each other within the *No Degree* outcome category. Thus, for the *No Degree* outcome category, whether a student was initially interested in pursuing a STEM major or not did not seem to matter much.

Within the non-STEM Degree outcome category, participants not interested in STEM (34.1%) were about twice as many in representation within the group compared to those interested in STEM (17.2%). This indicates that, for every three students in the non-STEM Degree outcome category, two of them had no initial interest in STEM when they declared their major in STEM. That is, the non-STEM Degree outcome category have significantly higher proportion of students who were initially not interested in STEM compared to those who were initially interested in STEM. Thus, a typical student selected from the non-STEM Degree outcome category is more likely to have indicated that he or she was not initially interested in STEM to begin with.

Similarly, within the STEM Degree outcome category, participants interested in STEM (59%) have more representation within the group than those not interested in STEM (41.3%). That is, the STEM Degree outcome category have significantly higher proportion of students who were initially interested in STEM compared to those who were not initially interested in STEM. Thus, a typical student selected from the STEM Degree outcome category is more likely to have indicated that he or she was initially interested in STEM to begin with. These findings suggest lack of independence between STEM persistence and completion status and STEM Interest.

To investigate the independence between STEM persistence and completion status and STEM Interest, a single factor Pearson's chi-square ($\chi 2$) test was applied to the crosstabs procedure (Table 9) to determine whether a correlation exists between STEM Interest and STEM persistence and completion status. The null hypothesis is that the two categorical variables are independent. The $\chi 2$ (30, 381, $p < .0001$, df = 2) test statistic was statistically significant and it can be concluded that STEM Interest is related to STEM persistence and completion status. A typical STEM degree seeking student who completed a degree in a STEM field tended to be interested in STEM whereas a typical STEM degree seeking student who switched majors and attained a non-STEM Degree tended to be not interested in STEM.

Analysis of Research Questions 4 and 5

Question 4: To what extent, if any, do student's demographic/background characteristics (i.e., gender, ethnicity, socio-economic status, and high-school grade point average) and students' contextual and environmental characteristics (i.e., academic integration, and institutional selectivity) affect their STEM persistence and degree completion status?

Question 5: Controlling for demographic and background characteristics and students' contextual and environmental characteristics, to what extent do individuals' non-cognitive attributes (i.e., self-efficacy, outcome expectations, and STEM interest) contribute to STEM persistence and degree completion status?

Because the outcome variable consists of three categories (completed STEM degree, completed non-STEM degree, No degree), I employed a multinomial logistic regression (MLR) to answer research questions 4 and 5. The control variables consist of students' personal inputs/background characteristics and contextual influences as represented by: gender, ethnicity/Minority status, Socioeconomic status, High School GPA, Academic Integration, and Institutional Selectivity. The noncognitive independent variables consist of the *Self-Efficacy*, *Outcome Expectations*, and *STEM Interest*.

The appropriate effect size for a MLR is the odds ratios for each predictor variable. The odds ratios are the ratios comparing the likelihood of being in a particular group to that of being in the reference group or baseline group. For this analysis, the third category (STEM Degree) was the reference group to which the other two groups (No Degree and Non-STEM Degree) were compared based on the predictor variables. Two logit equations were considered in the multinomial logistic regression to predict the log-odds of (1) No Degree status versus STEM Degree and (2) Non-STEM Degree status versus STEM Degree status. I also provided a logit for No Degree status versus STEM Degree status.

Model Fitting Information

Several statistical techniques were used to assess the model fit in the multinomial logistic regression. Table 10 shows the model fitting information for the multinomial logistic regression model. The difference between the -2 likelihoods for the intercept only model and for Model Two produces the chi-square of 164.664. This greater amount of change between the intercept only model and Model Two suggest a greater improvement in the fit for Model Two.

Table 10. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests			Pseudo R^2	
	-2 Log likelihood (Deviance)	Chi-Square	df	Sig.	Nagelkerke	McFadden
Intercept Only	13.319	0.000	0	.		
Model Two	1246.704	164.664	26	.000	0.237	0.112

Table 10 indicates that Model Two was significantly different from the intercept only model ($p < .001$) suggesting a good fit for Model Two against the intercept-only model (Tabatchnick & Fidell, 2007). The results show that there is improvement beyond the intercept only model.

Multinomial Logistic Regression Results

Table 11 presents the results of the multinomial logistic regression parameter estimates for the No Degree versus the STEM Degree earners (reference category) and the Non-STEM Degree versus the STEM Degree earners (reference category). Parameters with odds ratio greater than one increase the likelihood of student being identified with that outcome category of interest (No Degree or Non-STEM Degree) with respect to the reference category (STEM Degree).

Parameters with odds ratio less than one decrease the likelihood of student being identified with that outcome category of interest.

Table 11. Multinomial Logistic Regression: Parameter Estimates and Odds Ratio for STEM persistence and college degree completion status

Variable	**Reference Category**	**No Degree**		**Non-STEM**	
		Odds Ratio	**Std. Error**	**Odds Ratio**	**Std. Error**
Gender					
Male	*[Female]*	0.578*	0.233	0.415*	0.214
Underrepresented Minority Status					
Non-Underrep. Minority	*[URMs]*	0.629*	0.241	0.656*	0.248
Socioeconomic Status					
Low Social Econ. Status	*[High-SES]*	1.053	0.370	1.139	0.386
Mid Social Econ. Status		0.729	0.219	0.922	0.211
GPA for 9th – 12th grade					
GPA (0.00 – 2.00)	*[GPA (3.51 – 4.00)]*	3.281**	0.240	1.608	0.516
GPA (2.01 – 2.50)		2.947*	0.383	0.638	0.490
GPA (2.51 – 3.50)		2.565*	0.534	1.252	0.223
Academic Integration					
Low Acad. Integration	*[High-Integration]*	1.114	0.326	0.606	0.357
Mid Acad. Integration		0.796	0.237	0.703	0.216
Institutional Selectivity					
Low-Selective Institution	*[Highly Selective]*	2.448**	0.227	0.922	0.901
Noncognitive variables					
Self-Efficacy		0.775*	0.130	0.941	0.142
Outcome Expectations		0.749*	0.124	1.250⁺	0.134
No STEM Interest	*[STEM Interest]*	1.469**	0.222	2.156*	0.206

The reference outcome is ***STEM Degree*** **earners**
Overall Model Evaluation
Nelgelkerke R^2 = 23.7%

Significant variables are presented with asterisks +p<.10, *p<.05, **p<.01, ***p<.001
URMs represent Underrepresented Minority status
SES represents Socioeconomic Status

Multinomial Logistic Regression: No Degree status versus STEM Degree earners

Table 11 above shows that the control variables including gender, ethnicity/Minority status, high school GPA, and institutional selectivity were found to be statistically significant (p <.05) within the *Non-STEM Degree* outcome category. Male students were less likely (Odds

Ratio = 0.578, p<.05) to attained no degree or credential (as opposed to attaining a degree in STEM fields) when compared to their female peers. In other words, the odds of a male STEM student to attain no degree or credential (as opposed to attaining a degree in STEM fields) are 42% lower than a female STEM student, holding all other variables constant. Similarly, STEM students who were white or Asian ethnic groups (non-underrepresented minority backgrounds) were less likely (Odds Ratio = 629, p<.05) to attain no degree or credential (as opposed to completing a degree in STEM fields) than their underrepresented minority peers (Blacks, Hispanics, and all other minority groups). The odds of a non-underrepresented minority STEM student to attain no degree or credential (as compared to those who attained a degree in STEM fields) are 37% lower for underrepresented minority STEM students, holding all other variables constant.

Furthermore, students with a high school GPA lower than 2.0 are three times more likely (Odds Ratio = 3.281, p<.05) to not complete any degree or credential (as compared to students who completed a degree in STEM fields) than students with a high school GPA above 3.5. In addition, the degree of selectivity of the postsecondary institution was found to be statistically significant (Odds Ratio = 2.448, p<.05) for students who did not attain any degree or credential. This indicates that the relative odds of not completing any degree (as compared to completing a degree in STEM fields) will decrease by 41% for students who moved from a non-selective postsecondary institution to a selective postsecondary institution, controlling for other variables included in the model.

Similarly, I also examined the effects of the non-cognitive factors (self-efficacy, outcome expectations, and STEM Interest) on the outcome category of interest, after controlling for the independent variables. Students with no initial interest in pursuing a major in STEM field (No

STEM Interest) were more likely (Odds Ratio = 1.469, $p<.01$) to not earn any degree or credential at all as opposed to completing a degree in a STEM field. That is, they are about one and a half times more likely not to earn any degree or credential (as opposed to attaining a degree in STEM fields) when compared to students who expressed interest in pursuing college majors in STEM fields.

The results also indicate that students who scored higher on the self-efficacy scale were less likely (Odds Ratio = 0.775, $p<.05$) to have had a membership in the No Degree outcome category (as opposed to the STEM Degree completion category). Similarly, students who scored higher on the outcome expectations scale were less likely (Odds Ratio = 0.749, $p<.05$) to belong to the No Degree outcome category (as opposed to the STEM Degree completion category).

Multinomial Logistic Regression: Non-STEM Degree versus STEM Degree earners

As shown in Table 11, within the Non-STEM Degree outcome category, the gender variable was found to be statistically significant (Odds Ratio = .415, $p<.05$). This indicates that the odds of a STEM student switching into a Non-STEM major and earning a degree in a Non-STEM major (as compared to students who completed a degree in a STEM field) are 68% lower for male students than their female counterparts. Male STEM students have lesser odds of switching from their STEM majors and graduating with a Non-STEM degree compared to the female peers. Similarly, the odds of a non-underrepresented minority STEM student switching into a Non-STEM major and earning a degree in a Non-STEM discipline (as compared to students who completed a degree in a STEM field) are 34% lower for non-underrepresented minority STEM students than their underrepresented minority counterparts, holding all other variables constant.

Within the Non-STEM Degree outcome category, the noncognitive variable *No STEM Interest* was found to be statistically significant (Odds Ratio = 2.156, $p<.001$). This means that the odds of a STEM student switching into a Non-STEM major and earning a degree in a Non-STEM major as compared to those who completed a degree in a STEM field are about two times higher for students who expressed no interest in pursuing college majors in STEM fields than students who expressed interest in STEM. When compared to students who persisted and completed a bachelor's degree in a STEM field (STEM Degree), students who switched their major from STEM and completed a degree in a non-STEM field (Non-STEM Degree) showed less interest in pursuing a major in a STEM field ($p < .001$).

In addition, the non-cognitive factor of outcome expectations was found to be statistically significant (Odds Ratio = 1.250, $p<.10$). This indicates that students who scored higher on the outcome expectations scale were more likely to have switched their major from STEM fields and completed a degree in a non-STEM field (as oppose to STEM Degree) than students who scored lower on the outcome expectations scale.

Summary

This chapter presented the results and the statistical findings of the analysis used to address each of the five research questions of this study. I have presented the results using the appropriate methodology as described in Chapter 3. I have provided the results of both descriptive and inferential analysis as well as model evaluation techniques. I used ANOVA to detect mean differences in two continuous noncognitive variables (self-efficacy, and outcome expectations) among the three STEM persistence and college degree completion status groups (completed STEM degree, completed non-STEM degree, No degree). I also provided an in-depth analysis of two models using hierarchical multinomial regression. In Chapter 5, I will discuss the important findings, and conclude with the implication of the findings as well as recommendations for policy and future research.

CHAPTER V

CONCLUSION AND IMPLICATIONS

The purpose of this study was to provide a better understanding of the extent to which non-cognitive factors contribute to undergraduate students' persistence and college degree completion in Science, Technology, Engineering, and Mathematics (STEM) with particular attention to students enrolled in 4-year colleges and universities in the United States. Rather than focusing on the traditional cognitive ability and academic achievement measures of academic preparation such as high school GPA, SAT/ACT test scores, this study focused on the influence of the psychosocial factors on the decision-making processes of students' persistence.

The research questions that guided this study are as follow:

- Are there any differences in self-efficacy by STEM persistence and degree completion status?
- Are there any differences in outcome expectations by STEM persistence and degree completion status?
- Is there a relationship between STEM interest and STEM persistence and degree completion status?
- To what extent, if any, do student's demographic/background characteristics (i.e., gender, ethnicity, socio-economic status, and high-school grade point average) and students' contextual and environmental characteristics (i.e., academic integration, and institutional selectivity) influence their STEM persistence and degree completion status?

- Controlling for demographic and background characteristics and students' contextual and environmental characteristics, to what extent do individuals' non-cognitive attributes (i.e., self-efficacy, outcome expectations, and STEM interest) contribute to STEM persistence and degree completion status?

The analytical sample for this study was drawn from the Educational Longitudinal Study (ELS:2002-2012) dataset with the final sample used for analysis representing the 2002 cohort of 10th graders who declared a STEM major in college by 2006 and participated in the final wave of ELS in 2012.

Drawing on the Social Career Cognitive Theory (SCCT) as posited by Lent et al. (1994, 2000), the study examined the relationships among the non-cognitive factors through the SCCT pathways. The SCCT's framework does not only allow for inclusion of variables such as self-efficacy, outcome expectations, and STEM Interests which have not traditionally been considered in the college persistence literature, but also pays attention to background characteristics and contextual factors. In the following sections, a summary of the findings was discussed as well as implications for policy and recommendations for future research was considered.

Summary and Discussion of Findings

The findings of the present study suggest that although non-cognitive factors demonstrate modest improvements in predicting STEM persistence and college degree completion status, students' background characteristics and institutionally-specific contextual factors still play a significant role in predicting student outcomes. In other words, the present study indicates that non-cognitive factors added a modest value to the predictive regression model of STEM persistence and college degree completion status. A model based on control variables only (i.e., gender, ethnicity, socio-economic status, and high-school grade point average, academic integration, and institutional selectivity) explained approximately 20% of the variance in STEM persistence and college degree completion status, but this was improved to 24% when non-cognitive predictors of self-efficacy, outcomes expectations, and STEM interest were included. Although the increases in variance are only 4%, this small improvement in variance indicates that the model including the non-cognitive factors is a better predictor of STEM persistence and degree completion status than the model including only the control variables.

This study also provides a window into the noncognitive factors that might be crucial for answering key questions about the persistence and college degree attainment of students who have declared a major in a STEM field of study. This present study contributes to the emerging knowledge base about non-cognitive factors that influences STEM persistence and college degree completion status.

The importance of STEM Interest

Perhaps the most noteworthy finding from the present study is that students who expressed no initial interest in pursuing a major in STEM field (*No STEM Interest)* before the beginning of their postsecondary education, but declared a STEM major in college anyway, were more likely to switch their major from STEM field, and well over half of these STEM leavers ended up completing a non-STEM degree. Results from the present study shows that, about 60 percent of all students who express *no* initial interest in pursuing a major in STEM field (*No STEM Interest category*) before the beginning of their postsecondary education ended up switching their major from STEM field. In contrast, about 60 percent of all students who express initial interest in pursuing a major in STEM field (*STEM Interest category*) before the beginning of their postsecondary education completed a STEM bachelor's degree compared to only 40 percent of students who expressed no initial interest in pursuing a major in STEM field (*No STEM Interest category).*

Clearly, students who expressed initial interest in pursuing a major in STEM field (*STEM Interest category)* before the beginning of their postsecondary education, and declared a STEM major, were more likely to complete a STEM bachelor's degree. As indicated in the findings, STEM interest plays an essential role in predicting STEM persistence and degree completion. STEM interest represents a very useful tool in evaluating student's identification with the STEM field (Herrera and Hurtado, 2011). As such, STEM interest captures the degree of commitment students will be willing to expense on STEM related tasks. Herrera and Hurtado (2011) argued that student's identification with STEM can be viewed as their determination or intention to pursue a career in STEM field. Thus, those students who expressed STEM interest were the most likely students to graduate with a degree in a STEM major while students who had no STEM interest were the most likely to graduate with a degree in a non-STEM major.

Overall, this study results suggest that identifying STEM-interested students can serve as a helpful tool for predicting whether students will persist and graduate with a STEM bachelor's degree in college (Armstrong & Vogel, 2009; Byars-Winston et al., 2010; Lent et al., 2010; Tracey, 2010). This interesting result suggest that student's initial expressed interest in STEM before the beginning of postsecondary education will have a lasting effect on completion of their STEM degree. Therefore, it is important to foster students' interest in STEM even before starting a college career in STEM.

The importance of self-efficacy

The results of this study also confirm significant association between self-efficacy and STEM persistence and college degree completion status. The career counseling and vocational psychology research, for example, suggest that both interest and self-efficacy play significant role in the career decisions among high school and college students (Lent, Sheu, Gloster, & Wilkins, 2010; Milner et al, 2014). More importantly, this finding underscore the importance of enhancing students' confidence in their academic abilities to increase their interest in pursuing a STEM major. The finding of the present study indicated that when STEM students have high confidence in their academic abilities (especially in math and science), they are more likely to have a strong interest in pursuing a STEM major, which in turn is related to completing a degree in STEM field. The finding revealed that STEM interest and self-efficacy are critical factors in predicting STEM persistence and degree completion status. This indicate that stronger self-efficacy beliefs and high interest in pursuing a major in STEM field may lead to an increased likelihood of completing a degree in a STEM field. A possible explanation of the influence of these two noncognitive constructs may be that, as an implicit source of motivation, STEM interest reduces a students' psychological withdrawal behaviors and at the same time enhances task performance behaviors (Aryee & Chen, 2006). Thus, the high self-efficacy beliefs provide a favorable psychological context that motivate students' interest to pursue a major in a STEM field. The study, therefore, presents a viable approach to improving students' self -efficacy which may help cultivate stronger interest in pursuing STEM.

However, the current study also pointed out that most students who did not earn any degree at all also had a strong interest in pursuing a STEM major. These students, instead of switching and earning a non-STEM major either dropped out completely or failed to graduate within six years after their initial declaration of their college major in STEM. Clearly students with strong interest in pursuing STEM majors but having low self-efficacy and low outcome expectations have relatively at a higher risk of not attaining any degree within the six-year time frame after declaring themselves as STEM majors. Why did some students who indicated a desire or a strong interest in pursuing a major in STEM field and declared a major in STEM failed to complete any degree all (a possible type of functional failure)? That is, why is it that some students with high interest in STEM field were unable to function at the level which others with the same level of STEM interest were able to complete a STEM degree. As Bandura (1997) explained, low levels of self-efficacy may be a factor in the inefficient use of achieved skills. In other words, low self-efficacy may weaken the ability of these high STEM interest students to take advantage of their initial intention. At low levels of self-efficacy, students may feel helpless, anxious, or even depressed (Bandura, 1997). That is, self-efficacy is a major factor in the motivation process and its level may enhance or impede the motivation of an individual (Bandura, 1997; Brown et al., 2008; Pajares & Schunk, 2002). It can be concluded that, although STEM interest may serve as a strong incentive for completing a degree in STEM major, it may have negative effects when accompanied by low self-efficacy.

As indicated in the findings, STEM interest play an essential role in predicting STEM persistence and degree completion. Yet, STEM interest works more effectively when influenced by high self-efficacy. Students with high self-efficacy have tendencies that motivate them to choose to perform task that are more challenging, they set higher goals, and they usually stick to them. Student's self-efficacy beliefs determines how much effort they will be willing to expense on a given task, it determines how long they will be committed to the task and whether they will persevere when they face any challenges (Bandura, 1997). A strong sense of self-efficacy enhances their persistence and efforts to achieve a particular goal. In addition, students with strong self-efficacy beliefs put on their best effort in the face of difficulties, setbacks, and frustration (Bandura, 1997). On the other hand, students with low self-efficacy beliefs are usually doubtful about their capabilities and are more likely to quit easily when faced with challenges or they are more likely to settle with mediocre results. Thus, a strong sense of self-efficacy facilitates the decision-making process of students and plays a key role in the selection of actions and behaviors that will take them across the finish line of their intended major. High self-efficacy also influences certain fundamental elements such as goals and expectations and helps determine the level of effort that will be expended when faced with perceived obstacles and opportunities in the social environment (Pajares & Miller, 1994; Pintrich, 2000; Zimmerman & Bandura, 1994).

Overall, this study suggests a clear pathway for completing a degree in a STEM field by students who have declared a STEM major. This include those who have indicated a strong desire to pursue a major in STEM field of study, whose motivation was influenced by a high sense of self-efficacy coupled with a moderate level of outcome expectations. Students who indicated an interest in pursuing STEM major at college and whose desire was influenced by a strong sense of confidence in their academic abilities concerning math and science were more likely to compete a STEM degree within six years of declaring a STEM major. On the other hand, most STEM seeking students who switched major and graduated with a non-STEM degree tended to indicate that they had no desire to pursue a major in STEM field even before they began their postsecondary education.

The importance of outcome expectations

To succeed in college, students must be able to envision the likely outcome of their prospective action. The ability to envision the likely rewards or punishments of prospective action regulate human behavior. People's motivation to persist or sustain a certain action or behavior is a function of whether they expect a favorable or unfavorable results. Most people will work harder to gain the anticipated reward if they deem the behavior or action to be beneficial to them. On the other hand, people will be less motivated or will work less hard or may even want to give up if they anticipate the results to be aversive to them. Specifically, favorable outcome expectations will increase the strength of the motivation, whereas unfavorable outcome expectations will gradually weaken the effort.

The current findings suggest that outcome expectations may promote degree completion in general, but not necessarily STEM degree completion. Contrary to my expectation, student with very high outcome expectations tend to switch and complete a degree in a non-STEM field. The current findings indicate that students who scored higher on outcome expectations scale more likely to attain non-STEM degree (as opposed to STEM degree category) than students who scored moderately on the outcome expectations scale. Thus, very high outcome expectations was not predictive of earning a degree in STEM but was predictive of a non-STEM degree.

This study demonstrates that students who switched from STEM and completed a non-STEM degree were overly optimistic in their outcome expectations prediction, in that, these students were quite unrealistic in their outcome expectations estimates. This is based on the findings that the high outcome expectations of this group did not lead to STEM degree completion. Researchers have called this overly optimistic prediction of outcome expectations as *unrealistic optimism*. Unrealistic optimism occurs when an individual predicts a more favorable personal future outcome than what appropriate, objective standard suggests. Several researchers in psychology (e.g., Weinstein, 1980; Shepperd, Klein, Waters, & Weinstein, 2013) have argued that people show the same unrealistic optimism for both desirable events such as graduating from college, or getting married and undesirable events such as dropping out from college, diseases, and natural disasters. Individuals with unrealistic optimism unduly projects a more favorable personal outcome for themselves than the outcomes of their peers (Shepperd et al., 2013). Because unrealistic optimism may be evidenced by a very high positive outcome expectations, some researchers have argued that unrealistically high and unrealistically low outcome expectations may be detrimental to the individual (Tinsley, Bowman & Barich, 1993). Evidence from qualitative studies have shown that people might benefit even more from *moderate* outcome expectations than from unrealistically high or unrealistically low outcome expectations (Mason & Hargreaves, 2001; Wyatt, Harper, & Weatherhead, 2014).

Since the current study indicates that a high outcome expectations was not predictive of completing a STEM degree, but was predictive of the non-STEM degree group, students who completed a non-STEM degree need more control over setting realistic goals or expectations for themselves. They seem to probably lack the same intrinsic motivation that a high self-efficacy level can produce, so the motivation originating from the high outcome expectations was not strong enough to push them to study hard or to persevere in the face of obstacles in order to complete the degree. It is possible that these students had their motivation influenced mostly by external motivators which was not strong enough to push them through the STEM degree journey. It is also possible that the very high outcome expectations of students in the non-STEM category show that they had less internal locus of control (or were less regulated from within).

The importance of background, demographic and institutional characteristics

Regarding selected key variables (gender, ethnicity/Minority status, socio-economic status, High School GPA, institutional selectivity, and faculty integration), female students scored lower on the self-efficacy scale than male students, confirming the gender differences in self-efficacy levels by previous studies (Huang, 2013). Female students pursuing STEM major were at a greater risk than their male counterparts in not graduating with a degree in STEM field. Also, there were fewer female students in the number that declared STEM major. This may be due to female students facing gender stereotyping attitudes that discouraged them from pursuing and persisting in their declared major.

Prior academic achievement, as measured by student's high school grade point average (HSGPA), was also significant. Students who declared STEM major with a higher HSGPA had a significantly strong and positive likelihood of completing a degree in a STEM major relative to switching to a non-STEM major, or not attaining any degree at all. Students who attended selective colleges and universities had significantly better odds of completing their degree in a STEM major field. Similarly, interacting more frequently with faculty was a positive predictor of attaining a degree in a STEM field.

Implications for Policy and Practice

With the much attention paid to graduating STEM students, it was important to investigate whether non-cognitive factors (self-efficacy, outcome expectations, and STEM interest) have significant implications for successful completion of a degree in a STEM field. This research suggests that non-cognitive factors are related to whether students persist and complete a degree in STEM, or whether they leave a STEM major to complete a non-STEM degree or earn no degree at all. Understanding the mechanisms through which noncognitive factors influence STEM persistence and degree completion status can provide an informed basis for college campuses in creating conditions that will facilitate the development of these noncognitive skills as important sources of completing a STEM degree. These factors could also help colleges to identify students who will be more likely to complete their STEM degree. The practical implication of this study is that providing students with institutional nurturing that increases their self-efficacy will in turn help foster their interest in pursuing a major in STEM which will consequently increase their likelihood of completing their STEM degree.

The results of the study have clear implications for educators, administrators, and policymakers as the findings can be used to understand, plan, inform, and develop programs specifically aimed at improving persistence and degree completion in the STEM fields. This study shows that both cognitive (academic) and non-cognitive factors relate to STEM persistence and degree completion status. This study recommends that higher education administrators and policymakers design and develop programs that give joint attention to both cognitive (academic) and non-cognitive factors as well as take into consideration differences among the STEM student populations and available resources. However, given that most university and college campuses already have an early alert and monitoring system that focus mostly on academic performance indicators, this study proposes that institutions should focus more of their resources towards addressing deficiencies in student’s noncognitive attributes. This study demonstrated that there is a gap between STEM-seeking students who hope to complete a STEM degree (n =710) and those who actually completed a STEM degree (n = 371). Thus, there is a need for a comprehensive initiative which will bridge the gap. Based on review of relevant literature and the given the results of this study, I recommend that colleges and universities:

- Develop and implement noncognitive assessment measures (especially for self-efficacy and STEM interest) to more accurately determine the noncognitive skill levels of their incoming STEM students. University and colleges must require all incoming STEM students to participate in a non-cognitive assessment survey with exemption given only on a case-by-case basis. Universities and colleges can set up a non-cognitive assessment committee to give guidance to the implementation of this recommendation.
- Create a “Non-Cognitive Behavioral Intervention (NCBI)” program designed to change STEM student’s negative or unrealistic thought patterns and behaviors with interfere with their academic progress and persistence. A NCBI program may aim at positively influencing student’s self-efficacy, interest, and other emotional and affective functioning. This program should be responsible for engaging targeted STEM-related professional development activities and strategies for faculty, staff, and administrators. Students whose diagnostic non-cognitive assessment shows a deficiency must be required to participate in this NCBI program (similar to first-year experience programs) established for STEM students. This program must provide critical noncognitive skills training essential to success in STEM fields.
- Incentivize STEM faculty to redesign their curriculum to support addressing non-cognitive needs of students. STEM faculty who engage in utilizing research and best practices and intervention program improvements to increase STEM outcomes should be rewarded. STEM institutions cannot continue to place students into traditional classes

that continue to use the same mode of teaching that had failed to address student's noncognitive concerns. Alternative methods of curriculum delivery that considers best practices must be encouraged by college and university administrators.

- Establish a strategic professional development opportunity for all STEM faculty so that they will be better prepared to respond to ever evolving non-cognitive skill needs of students. STEM faculty may need a consistent productive professional development activities that specifically addresses students noncognitive needs. STEM part-time faculty should be supported by professional development activities related to improving student's noncognitive skills.
- Incentivize students with low noncognitive skills to participate in a non-cognitive assessment plan which requires students to be actively engaged in addressing their own non-cognitive skill deficiencies within the first semester of their entry into college. The institution can intervene if student has not taken the assessment by the second semester of college and require that they take the assessment in order to maintain their enrollment.

The findings of the current study indicate that lower levels of students' noncognitive skills sets is of great concern considering the evidence that students with lower levels of the noncognitive attributes were more likely not to complete any degree. Lower levels of self-efficacy may suggest that students perceive STEM coursework to be difficult, and this may hinder the development of their interest in pursuing a major in STEM field. Postsecondary institutions should implement programs that would help develop STEM students' self-efficacy experiences in the context of STEM coursework.

Apart from STEM interest, the results regarding the high levels of non-cognitive factors of self-efficacy and outcome expectations suggest that these noncognitive attributes are vital for degree completion, both for STEM and for non-STEM fields. Thus, the non-cognitive factors that drives STEM students to complete a degree in STEM fields are also highly necessary skills required to persist and complete a non-STEM degree. Students with low levels of outcome expectations and self-efficacy will be unable to fulfil the high demands and rigorous academic work for meeting the demands of completing a STEM degree.

Focusing attention on intervention efforts geared towards increasing students' interest in pursuing STEM majors at the K-12 level may pay off greater dividends in building a sustainable future STEM workforce. This study provides information that can result in a higher quality educational practice in the context of clarifying the factors which would form the backbone of a model of success in a STEM field, success here defined as completing a degree in STEM.

As higher education institutions continue to face increasing challenges to retain and graduate STEM degree seeking students, expanding the search for predictors beyond the traditional predictors of STEM persistence and college degree completion status can be useful. For example, additional study incorporating financial aid and other factors are strongly recommended. Institutions can target students who for example indicated that they have no desire to pursue a major in STEM field yet declared a STEM major with intervention and development programs that will encourage their STEM interest. In addition, this approach will help these students to build a stronger their academic confidence or self-efficacy belief system so as to improve their chances of succeeding in STEM.

Recommendations for Future Research

An understanding of the role that non-cognitive factors play in STEM persistence and degree completion is important to researchers and policymakers who hope to assist STEM students achieve their main goal—completing a degree in a STEM major field. University and higher educational researchers and policymakers need to understand what factors predict STEM students' successful completion of their STEM degree since these students will play an important role in the technological advancement and global competitiveness of the United States. The finding of the current study shows that when STEM students have high confidence in their academic abilities, they are more likely to have a high interest in pursuing a STEM major, which in turn is related to completing a degree in STEM field.

Additional research should be conducted to expand this line of research. Future research can explore more about other institutional/environmental factors (such as private or public institutions, community colleges, etc.) to analyze the relationship between the noncognitive variables of self-efficacy, outcomes expectations, and STEM interest and their effect on the STEM persistence and degree completion status of students. Furthermore, future research incorporating financial aid and other sources of funding are strongly recommended.

It is imperative that future research will continue to identify further non-cognitive characteristics of students that are vital to students' success in STEM for intervention efforts in STEM to be effective. It is also highly recommended that qualitative research should be conducted to investigate as to why students who indicated that they have no desire to pursue a major in STEM field (no STEM interest) decided to declare a major in STEM.

The present study also found that STEM interest is influenced by a strong sense of self-efficacy. However, there is little empirical research on role of self-efficacy in completing a STEM degree. This is, the basis of STEM students' self-efficacy has not been fully investigated. Simply knowing that a strong sense of self-efficacy may influence STEM interest which in turn may lead to completing a degree in STEM is not enough. Thus, future research should identify factors that may contribute to the self-efficacy of STEM students and incorporate it into the model.

The paucity of relevant measures for noncognitive attributes in the national educational databases posed a severe challenge for this type of research. It is recommended that future nationally reprehensive educational database should include an assorted set of noncognitive assessment measure. With the growing number of studies focusing on the role of noncognitive factors on educational outcomes, expanding the national databases with additional noncognitive variables will be invaluable to educational researchers. Similarly, future studies must put effort into identifying valid survey items that could constitute as measures of certain key noncognitive factors.

One finding of the present study is that the institutional environment in which the student is enrolled matters when considering whether a STEM student will end up completing a degree in a STEM field of study. The current study found that the degree of selectiveness of the postsecondary institution in which the student is enrolled was statistically significant. This indicates that the relative odds of not completing any degree (as opposed to completing a degree in STEM fields) will decrease by 47% if a student enroll in a selective postsecondary institution, controlling for all covariates included in the model. The explanation for this result is that institutions differ widely in the resources that they allocate for STEM education and selective institutions do have more funding and resources available to them which shapes the extent to which students in their institutions engage in and excel in STEM. This finding is supported by prior research which indicate that the characteristics of institutional context and climate influences student persistence in STEM. (Chang et al., 2014; Hurtado and Carter, 1997). It is therefore recommended that the federal government will support financially the STEM educational efforts of the nonselective institution.

Conclusion

Despite the acknowledged importance of noncognitive attributes, relatively little research has been conducted concerning the type of noncognitive attributes that are most influential on the persistence and college degree completion of STEM students. The significant lower levels of the non-cognitive factors among those students with no degree suggest that the no degree students did not have the relevant non-cognitive skills that will effectively sustain their academic effort towards completing a degree. The results of this study clearly suggest that certain types of noncognitive attributes have consequences for persistence and college degree completion of STEM students. The findings of this imply that noncognitive attributes matters in STEM persistence and degree completion.

This study showed evidence of the possibility of enhancing self-efficacy beliefs of students to increase students interest in pursuing a major in STEM field which consequently may influence STEM degree completion so that the nation may benefit from the increased supply of its STEM workforce due to the increase level of STEM degree completion. Results of the study revealed these three general findings about the three noncognitive factors. First, students with strong interest in pursuing a STEM major, a high Self-Efficacy, and a moderate Outcome Expectations are more likely to persist and complete their college degree in their declared major in STEM field. Students who reported that they had no interest in pursuing a STEM major yet declared a STEM major in their postsecondary education, and who have high Self-Efficacy and High Outcome Expectations are more likely to switch to a non-STEM major and persist to complete a degree in a non-STEM field. Third, students with strong STEM Interest, but low Self-Efficacy, and low Outcome Expectation were more likely to not attain any degree or credential. While prior research has suggested that self-efficacy beliefs are fundamental to students' interest to pursue STEM fields of study (Wang, 2013), this study offers additional empirical evidence for linking interest in pursuing a STEM field of study to STEM persistence and degree completion status. Self-efficacy beliefs play a significant and positive role in shaping students STEM interest, and through STEM interest in pursuing STEM field of study, self-efficacy has indirect effect on STEM persistence and degree completion status.

In closing, this research has provided an in-depth insight into the predictive role of self-efficacy, outcome expectations, and STEM interest on the persistence and degree completion of college students who declared a major in STEM field of study. The study provides a critical linkage between theory, research, and practice necessary to facilitate intervention initiatives to meet the present needs of STEM students. It is my hope that these research findings would lead to policies, practices and strategies that will eventually result in better academic outcomes for our STEM students.

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APPENDIX A

ELS VARIABLES USED IN THE STUDY

Table A.1. Summary of ELS variables in the study

Variable Name	Questionnaire items/Description	ELS variable label	Recoded as
DECLARED MAJOR	Student's post-secondary major in 2006	F2MJR2_P F2MAJOR2 recorded students' actual majors two years after high school	STEM = 1 non-STEM=0
4-YEAR ENROLLMENT	Reported postsecondary enrollment in either a 2- or 4-year college or not at any point within two years after high school graduation was examined.	F2B07	4yr = 1 non-4yr=0
STEM INTEREST	Field of study respondent would most likely pursue when beginning at the first postsecondary institution.	F2B15	STEM Interest = 1, Non-STEM Interest = 0.
SELF-EFFICACY	Can understand difficult math texts	BYS89B	
	Can understand difficult math class	BYS89L	
	Can master math class skills	BYS89U	
	Items based on 4-point Likert scales with 4 indicating almost always and 1 indicating almost never		
OUTCOME EXPECTATIONS	Studies to get a good grade	BYS89D	
	Studies to increase job opportunities	BYS89H	
	Studies to ensure financial security	BYS89P	
	Items based on 4-point Likert scales with 4 indicating almost always and 1 indicating almost never		
GENDER	Female	F1SEX	Female = 1 Male = 0
ACADEMIC INTERACTIONS	Talk with faculty about academic matters outside of class	F2B18A	
	Items based on 3-point scales with 3 indicating often and 1 indicating never		
SOCIO-ECOMONIC STATUS	Composite variable of mother's education, father's education, family income, mother's occupation, and father's occupation First follow-up SES quartile f1ses1qr 1=Lowest quartile, 2=Second quartile, 3=Third quartile 4=Highest quartile	FSES1QR	1=Low (Q1) 2=Mid (Q2+Q3) 3=High (Q4)

SELECTIVITY*	Selectivity of attended postsecondary institution: 1= Highly selective, 4-yr institution 2= Moderately selective, 4-yr inst 3= Inclusive, 4-yr institution 4= Selectivity not classified, 4yr inst		1 = Highly selective 0 = Not selective
	Credential type: 1= Undergraduate certificate or diploma 2= Associate's Degree 3= Bachelor's Degree 4= Post-baccalaureate certificate 5= Master's Degree 6= Post-Master's certificate 7= Doctoral Degree - research/scholarship 8= Doctoral Degree - professional practice 9= Doctoral Degree - other	F3ICREDTYPE_1	
RACE/ETHNICITY	Race/ethnicity Hispanic White Asian African American Other races	F1RACE Hispanic =1, all other = 0 White= 1, all other = 0 Asian= 1, all other = 0 African American= 1, all other = 0 American Indian, Alaskan native, Native Hawaii/Pac. Islander more than one race= 1, all other = 0	

*Institutional Selective scale used in the current study was based on the ELS:2002 selectivity measure which used the 2010 Carnegie Classification of Institutions of Higher Education System. In the ELS:2002 dataset, institutions were classified under three broad categories based on the distribution of students' entrance examination scores. They were: (1) Highly selective 4-year institutions—which represent the test scores that will place students in roughly the top fifth of baccalaureate institutions; (2) Moderately selective 4-year institutions —which represent the test scores that will place students in roughly the middle two-fifths; and (3) Inclusive 4-year institutions —which extends educational opportunity to a wide range of students with respect to academic preparation and achievement.

Source: Department of Education, Institute of Education Sciences, National Center for Education Statistics. Education Longitudinal Study of 2002 (ELS:2002) Third Follow-up Public-Use File (NCES 2014-365)

APPENDIX B

SUMMARY OF SIGNIFICANT RESULTS

Table B.1. Summary of significant findings for research questions 1-3(pairwise comparison)

Dependent	Multiple Comparison Between:	Significant findings from regression analysis
Self-Efficacy	***no Degree*** students versus ***STEM Degree*** earners	• A statistically *significant* pairwise difference between the **mean *self-efficacy* scores** of students who had ***no Degree*** and students who completed a ***STEM Degree***
	no Degree students versus ***Non-STEM Degree*** earners	• A statistically *significant* pairwise difference between the **mean *self-efficacy* scores** of students who had ***no Degree*** and students who completed a ***non-STEM Degree***
Outcome expectations	***no Degree*** students versus ***Non-STEM Degree*** earners	• A statistically *significant* pairwise difference between the **mean *outcome expectations*** scores of students who had ***no Degree*** and students who completed a ***Non-STEM Degree***
	Non-STEM Degree earners versus a ***STEM Degree*** earners	• A statistically *significant* pairwise difference between the **mean *outcome expectations*** scores between students who had ***no Degree*** and students who completed a ***STEM Degree***
	Non-STEM Degree earners versus a ***STEM Degree*** earners	• A statistically *significant* pairwise difference between the **mean *outcome expectations*** scores between students who completed a ***non-STEM Degree*** and students who completed a ***STEM Degree***
STEM Interest	***no Degree*** students versus completed a ***Non-STEM Degree*** students	• A typical STEM degree seeking student who completed a degree in a STEM field tended to be a participant interested in STEM whereas a typical STEM degree seeking student who attained a non-STEM Degree tended to be participants who were not interested in STEM.

Table B.2. Summary of significant findings for research question 3 (Multinomial logistic regression models)

Comparison	Predictors	Significant findings from regression analysis
No degree *versus* ***STEM degree earners***	Key Covariates only (including institutional selectivity and faculty integration)	1) Female students more likely to attain no degree (as opposed to STEM degree) than male student 2) Underrepresented minority ethnic groups more likely to attain no degree (as opposed to STEM degree) than non-underrepresented minority students 3) Students with GPA below 3.5 more likely to attain no degree (as opposed to STEM degree) than students with high school GPA greater than 3.5. 4) Students who attended highly selective institutions more likely to attain STEM degree (as opposed to no degree) than students who attended low selective institutions.
	Self-Efficacy, *Outcome Expectations* and *STEM Interest* after controlling for key covariates	1) Students who scored higher on self-efficacy scale more likely to attain STEM degree (as opposed to no degree) than students who scored lower on self-efficacy scale. 2) Students who scored higher on outcome expectations scale more likely to attain STEM degree (as opposed to no degree) than students who scored lower on outcome expectations scale. 3) Students with no initial interest in pursuing a major in STEM field (*No STEM Interest*) were more likely to earning *no degree* or credential at all as opposed to completing a degree in a STEM field.
Non-STEM degree *versus* ***STEM degree***	Key Covariates only (including institutional selectivity and faculty integration)	1) Female students more likely to attain Non-STEM degree (as opposed to STEM degree) than male student.
	Self-Efficacy, *Outcome Expectations* and *STEM Interest* after controlling for key covariates	1) Students who scored higher on outcome expectations scale more likely to attain *non-STEM degree* (as opposed to STEM degree) than students who scored lower on outcome expectations scale. 2) Students who expressed no initial interest in pursuing a major in STEM field (*No STEM Interest*) were more likely to attain *non-STEM degree* (as opposed to STEM degree) than students who express an initial interest in pursuing a major in STEM field (*STEM Interest*)

APPENDIX C

GRAPHICAL REPRESENTATION OF STEM DEGREE COMPLETION BY PREDICTOR VARIABLES

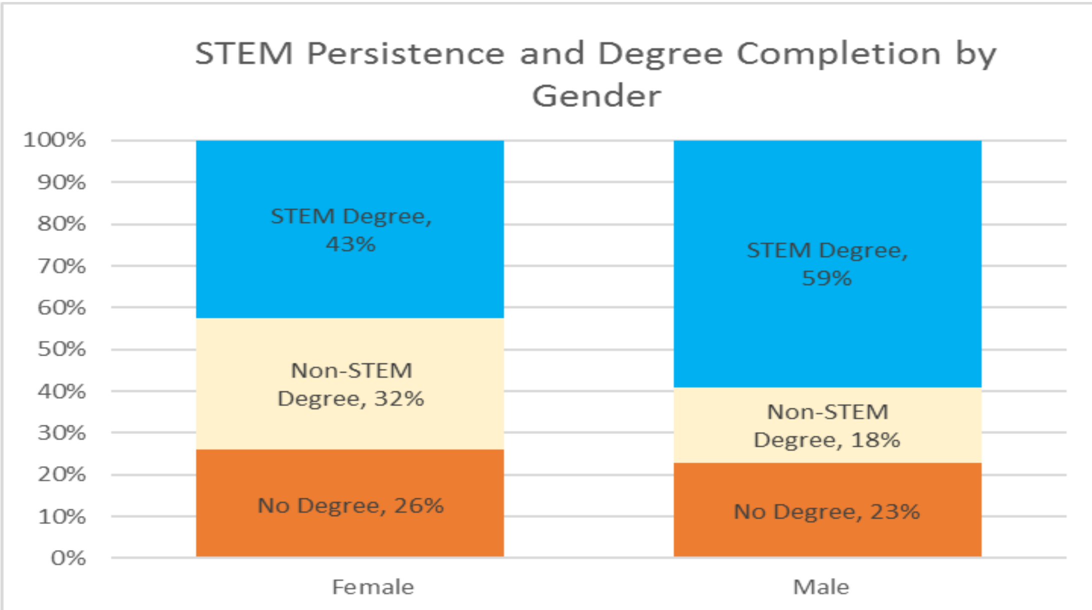

Figure A.1. The graphical representation of the distribution of STEM persistence and completion status by Gender.

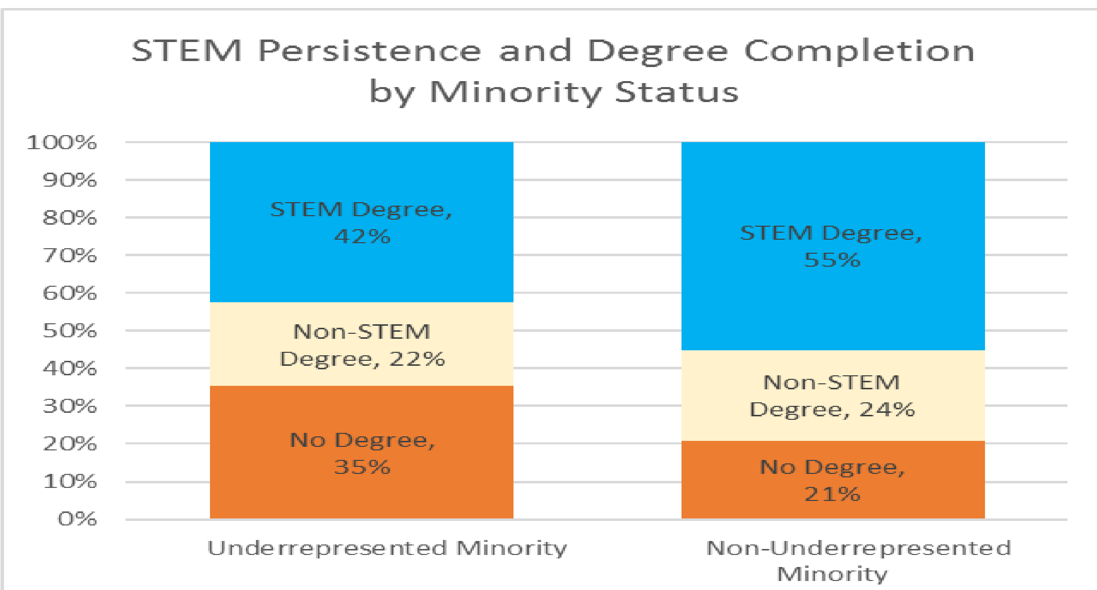

Figure A.2. The graphical representation of the distribution of STEM persistence and completion status by Underrepresented Minority Status.

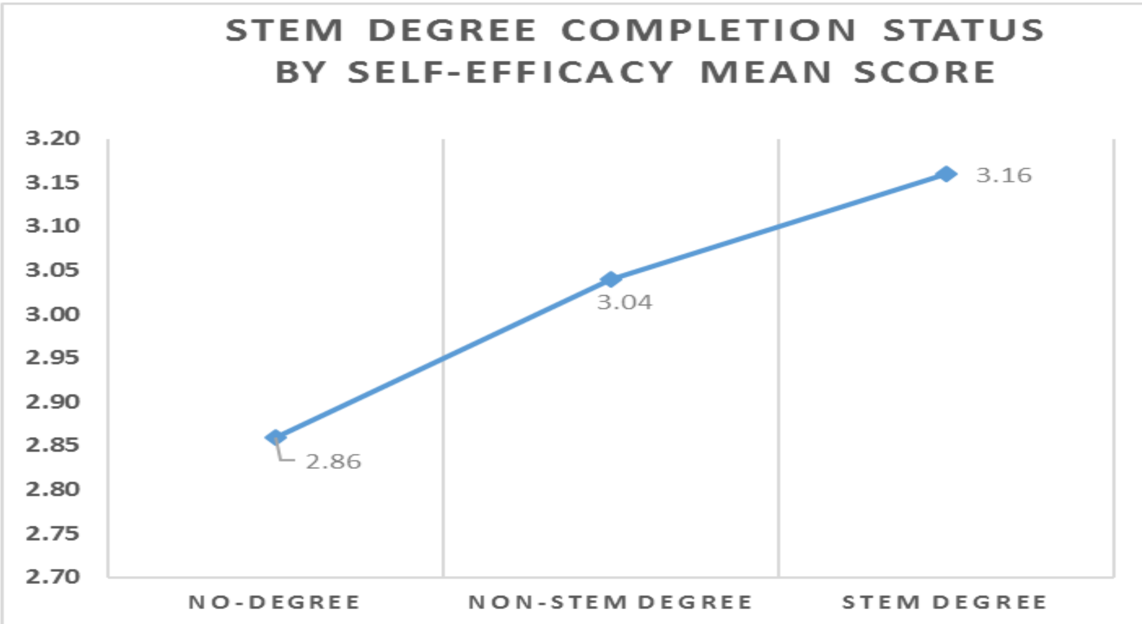

Figure A.3. The graphical representation of the distribution of STEM persistence and completion status by Self-Efficacy.

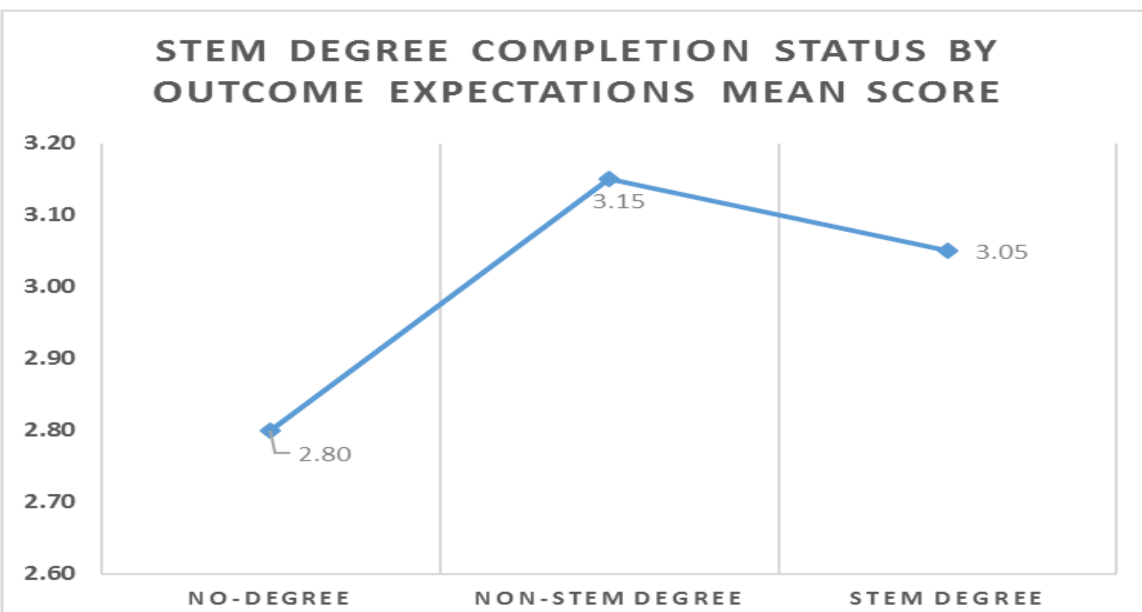

Figure A.4. The graphical representation of the distribution of STEM persistence and completion status by Outcome Expectations.

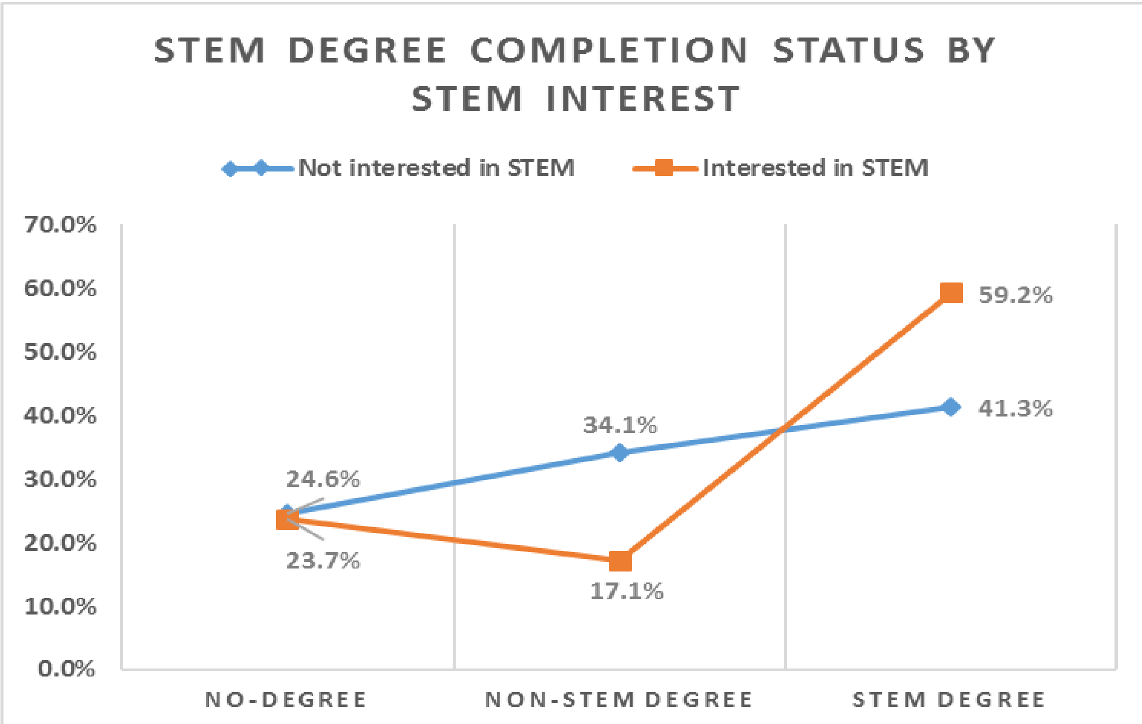

Figure A.5. The graphical representation of the distribution of STEM persistence and completion status by STEM Interest.

APPENDIX D

DETAILS OF SOME KEY VARIABLES

DETERMINATION OF STEM INTEREST VARIABLE

One indicator of STEM interest came from a survey question in the ELS:2006 dataset which asked students to indicate what field of study they would most likely pursue when beginning at the first postsecondary institution (F2B15 "When you began your post-secondary education, what field of study did you think you were most likely to pursue?"). Students who are more likely to pursue a STEM related postsecondary major (coded 1=yes) were differentiated from those who are more likely to pursue non-STEM majors (coded 0=no).

FIELD OF STUDY MOST LIKELY TO PURSUE UPON ENTERING POSTSECONDARY SCHOOL (F2B15):

The F2B15 variable was directly taken from the second follow-up F2 interview. Respondents were asked, “When you began your postsecondary education, what field of study did you think you were most likely to pursue?”

The 16 response options are as follows:

1. Business or marketing;

2. Health (for example, medical technology, nursing, pre-med);

3. Education (for example, teaching);

4. Engineering or engineering technology;

5. Computer or information sciences;

6. Natural sciences or mathematics (for example, biology, physics, or statistics);

7. Environmental studies;

8. Social sciences or social work (for example, psychology, history, political science);

9. Architecture, design, or urban planning;

10. Fine arts (for example, music, theatre, dance);

11. Humanities (for example, English, philosophy, foreign languages);

12. Communications (for example, journalism);

13. University transfer or general education;

14. Other vocational programs (for example, cosmetology, culinary arts, or construction);

15. Other; and

16. Don't know/undecided.

ELS VARIABLE TO DETERMINE OUTCOME VARIBLE

- The first degree earned by students (F3ICREDTYPE_1) and the major associated with the degree (F3ICREDFIELD_1) was examined to make the outcome variable determination. Since the sample for this study is only for 4-year postsecondary institutions, degrees earned was counted only if student achieved at least a bachelor's degree or higher.
- If postsecondary major was in a STEM field of study and the associated college degree was at least a bachelor's, the student was categorized as STEM Degree.
- If the student earned at least a bachelor's degree in a subject other than STEM then the student was categorized as categorized as Non-STEM Degree.
- If the student earned no college degree, then the student was categorized as No Degree.
- Both Non-STEM and No Degree outcomes was classified as non-persisters in STEM field.

ELS VARIABLE TO DETERMINE WHETHER STUDENT DECLARED MAJOR

- Variable Name(s): F2B22: Now in 2006, have you declared a major yet at [F2PS2006]?

  0 = Not in a degree program

  1 = Declared major

  2 = Declared double major

  3 = Not yet declared

- Variable Name(s): F2B23A: What is your [first] major or field of study?
- Variable Name(s): F2B24: What is your second major or field of study? (Please do not include a minor.)

APPENDIX E

FIELDS OF STUDY USED AS STEM

The classification of STEM and non-STEM was based on an NCES report authored by Chen and Weko (2009). Tthe following fields were categorized as STEM in ELS:2002:

- Mathematics and statistics (2-digit CIP 27),
- Agricultural/natural resources/related(2-digit CIP 01, CIP 03),
- Biological/biomedical sciences(2-digit CIP 26),
- Physical sciences (2-digit CIP 40), science technologies/technicians (2-digit CIP 41),
- Engineering technologies/technicians, (2-digit CIP 15)
- Mechanical/repair technologies, (2-digit CIP 47) and
- Computer/information sciences/support technicians. (2-digit CIP 11)
- *Engineering, Physical Science and Math-related Fields*
- Computer/Information Sciences/Support tech (2-digit CIP 11)
- Engineering (2-digit CIP 14)
- Engineering Technologies/Technicians (2-digit CIP 15)
- Mechanic and Repair Technologies/Technicians (2-digit CIP 47)
- Mathematics and Statistics (2-digit CIP 27)
- Physical Sciences (2-digit CIP 40)
- Science Technologies/Technicians (2-digit CIP 41)
- Agriculture and Related Sciences (2-digit CIP 01)
- Natural Resources and Conservation (2-digit CIP 03)
- Biological and Biomedical Sciences (2-digit CIP 26)
- Precision Production (2-digit CIP 48)

APPENDIX F
DETAILS OF ANALYTICAL SAMPLE AND NON-ANALYTICAL SAMPLE DATA

TABLE F.1. ANALYTICAL SAMPLE: DESCRIPTIVE STATISTICS OF STUDENTS WHO DECLARED STEM MAJORS (N=710)

Variable	Category	Number in Sample	Percent in Sample (%)
Gender	Female	294	41.4%
	Male	416	58.6%
Ethnicity	White	430	60.6%
	Asian	124	17.5%
	African American	75	10.6%
	Hispanic	54	7.6%
	Others + multi-racial groups	27	3.8%
Socioeconomic Status (SES)	Low-SES	63	8.3%
	Mid-SES	280	40.2%
	High-SES	367	51.5%
STEM degree completion	Completed STEM Degree	371	52.2%
	Completed a non-STEM Degree	169	23.7%
	No Degree	171	24.1%

TABLE F.2. MISSING DATA: DESCRIPTIVE STATISTICS OF STUDENTS WHO DECLARED STEM MAJORS (N=124)

Variable	Category	Number in Sample	Percent in Sample (%)
Gender	Female	56	45.2%
	Male	68	54.8%
Ethnicity	White	63	50.8%
	Asian	26	21.0%
	African American	16	12.9%
	Hispanic	11	8.9%
	Others + multi-racial groups	8	6.4%
Socioeconomic Status (SES)	Low-SES	18	14.5%
	Mid-SES	60	48.4%
	High-SES	46	37.1%
STEM degree completion	Completed STEM Degree	72	58.1%
	Completed a non-STEM Degree	31	25.0%
	No Degree	21	16.9%

TABLE F.3. NON-STEM SAMPLE: DESCRIPTIVE STATISTICS OF STUDENTS WHO DECLARED NON-STEM MAJORS IN 2016 (N=3335)

Variable	Category	Number in Sample	Percent in Sample (%)
Gender	Female	2093	62.8%
	Male	1242	37.2%
Ethnicity	White	2267	68.0%
	Asian	315	9.4%
	African American	318	9.5%
	Hispanic	300	8.9%
	Others + multi-racial groups	135	4.0%
Socioeconomic Status (SES)	Low-SES	352	10.6%
	Mid-SES	1465	43.9%
	High-SES	1518	45.5%