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PREDICTING UNDERGRADUATE RETENTION IN STEM MAJORS BASED ON DEMOGRAPHICS, MATH ABILITY, AND CAREER DEVELOPMENT FACTORS

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
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ABSTRACT

Science, technology, engineering, and math (STEM) fields are currently facing a crisis with respect to filling jobs with qualified workers (NSF, 2013; NAS, 2011). While advancements in these industries have translated into job growth, post-secondary declaration and retention rates within STEM majors lag behind industry needs (Carnevale et al., 2011; Chen, 2013; Koenig et al., 2012). Although researchers previously investigated demographic variables and math-related variables in the context of STEM retention (Beasley & Fischer, 2012; CollegeBoard, 2012; Cundiff et al., 2013; Gayles & Ampaw, 2014; Le et al., 2014; Nosek & Smyth, 2011; Riegle-Crumb & King, 2010), the need exists for additional research examining the impact of career-related variables (Belser et al., 2017; Folsom et al., 2004; Parks et al., 2012; Reardon et al., 2015). Additionally, prior STEM retention research primarily focused on students with declared STEM majors, as opposed to undeclared students considering STEM majors.

In the present study, the researcher sought to determine the degree to which demographic variables (gender and ethnicity), math ability variables (SAT Math scores and Math Placement Test--Algebra scores), and career development related variables (initial major, STEM course participation, and Career Thoughts Inventory [CTI] change scores) could predict undergraduate retention in STEM for participants in a STEM recruitment and retention program. Using binary logistic regression, the researcher found that initially having a declared STEM major was the best predictor of STEM retention. Higher scores on math variables consistently predicted higher odds of STEM success, and the data revealed higher odds of STEM retention for ethnic minority

students. Gender only showed to be a significant predictor of STEM attrition with the undecided students with first-to-third year retention. Finally, larger decreases in CTI scores predicted increased odds of STEM retention. Implications from the findings relate to a variety of professionals from higher education, counseling, and research. The findings provide guidance and new perspectives on variables associated with better rates of STEM retention, and as such, inform STEM initiatives targeting undergraduate STEM recruitment and retention.

This dissertation is dedicated to the lives lost, broken, or changed in Orlando, Baton Rouge, and South Louisiana during Summer 2016, when hatred, violence, and natural disasters tested the strength of these communities. I am proud to have called each of these places home and will continue to be inspired by your resilience, perseverance, and persistence.

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CHAPTER I: INTRODUCTION

Despite advancements and job growth within science, technology, engineering, and math (STEM) fields, the United States currently faces a crisis with respect to filling these jobs with qualified individuals (National Science Foundation [NSF], 2013; National Academy of Sciences [NAS], 2011). In addition to job creation, the rise in retirements among the Baby Boomer generation and high attrition rates within STEM degree programs at post-secondary institutions both are predicted to contribute to a deficit of nearly three million skilled STEM workers by 2018 (Carnevale, Smith, & Melton, 2011). Whereas the impact of this crisis may not be completely universal, Xue and Larson (2015) posited that the deficits vary across STEM disciplines, worker education levels, and geographic locations around the country. Moreover, disparities also exist when the numbers are broken down by race and gender (National Science Board, 2015).

Carnevale et al. (2011) identified high attrition rate for undergraduates in STEM majors as one key problem contributing to the STEM crisis. In one report, less than 30 percent of undergraduates declared a STEM major at four-year institutions, and of these students, approximately half left their STEM major prior to graduation either by changing their majors or by leaving college altogether (Chen, 2013). Variance exists in STEM retention rates depending on the post-secondary institution, with some reporting closer to 30 percent (Koenig, Schen, Edwards, & Bao, 2012). To combat the low rates of students earning STEM degrees, post-secondary institutions have begun providing initiatives specifically targeting recruitment and

retention for undergraduate STEM degrees (Bouwma-Gearhart, Perry, & Presley, 2014; Defraine, Williams, & Ceci, 2014). The goals of such programs include capturing students into STEM degree programs and providing them with support to promote their success with a desired outcome of increased degree attainment. Many of these programs also include initiatives to increase participation in STEM for underrepresented populations, such as women and students of color (Carnevale et al., 2011; Palmer, Maramba, & Dancy, 2011).

Within the present study, the researcher sought to investigate retention and attrition rates for one such STEM program at the University of Central Florida (UCF). The UCF COMPASS Program (*Convincing Outstanding Math-Potential-Admits to Succeed in STEM*) targets first-time college students who have a potential interest in STEM but have not confirmed their major choice. Some students have an uncommitted interest in STEM based on hobbies, parent or guardian careers, and/or experiences in high school coursework. The program provided math support, mentoring, and research opportunities, which are not uncommon in undergraduate STEM initiatives (Bouwma-Gearhart, Perry, & Presley, 2014; Defraine, Williams, & Ceci, 2014). A uniqueness of the COMPASS Program was the inclusion of a STEM-focused Career Planning Class as a career development intervention. The current study included career-related variables, in addition to demographics and math ability, to determine the extent to which these variables could predict whether or not undergraduates would be retained in a STEM major for their first two years of college. As the program incorporates a career development focus, the researcher framed the proposed study on previous literature and research in the areas of

undergraduate retention in STEM majors and career development, as well as several theoretical models of career development.

Theoretical Foundation

Of the numerous career development theories, four in particular contributed to the framework of this study: (a) the Theory of Circumscription, Compromise, and Self-Creation (Gottfredson, 1981); (b) the Theory of Vocational Choice (Holland, 1973); (c) Social Cognitive Career Theory (Brown & Lent, 1996; Lent, 2005; Lent & Brown, 2002); and (d) the Cognitive Information Processing Approach (Peterson, Sampson, & Reardon, 1991; Peterson, Sampson, Reardon, & Lenz, 1996; Sampson, Lenz, Reardon, & Peterson, 1999; Peterson, Sampson, Lenz, & Reardon, 2002). Each theory offered a perspective on at least one of the constructs of interest for the study, and together they created a framework for understanding processes and issues within STEM career development.

Theory of Circumscription, Compromise, and Self-Creation

Linda Gottfredson's Theory of Circumscription, Compromise, and Self-Creation (Gottfredson, 1981) defines the process by which individuals begin to eliminate career options that are not seen as good matches or that are seen as being outside the scope of possibility for an individual. Although the stage models of this theory do not directly overlap with the average age range of undergraduate students, the theory does shed light on processes occurring during childhood that may have long-term implications on self-concept and career choice, particularly

with regard to gender roles and social prestige (Zunker, 2016). Gottfredson explained that children begin to narrow their career options in early childhood based on interactions with society, and this process occurs in four stages. During the second stage, societal gender norms and stereotypes influences individuals' conceptualization of careers (Zunker, 2016). This stage in particular offered insight into the gender disparities that exist within STEM fields, which may be the result of a lack of representation for females within STEM.

Gottfredson (1981) found that individuals are more likely to compromise, or concede, their area of career interest before the sex type for a career if there is a large perceived discrepancy between what they want to do and what they perceive is possible. Young females who do not see other females like them in STEM careers may begin to perceive these careers as not easily attainable. As such, if something is not done to intervene with females eliminating STEM career options based on a perceived lack of representation within STEM careers, this cycle may continue to negatively impact females. Although Gottfredson's theory does not specifically address ethnicity in the same way that it does address gender, the theory did provide context on how a lack of representation in STEM could affect underrepresented ethnic or racial groups.

Theory of Vocational Choice

John Holland's (1973) Theory of Vocational Choice is one of the most widely used and widely studies career theories (Curry & Milsom, 2014). Holland theorized that individuals fall within one of six types: (a) Realistic, (b) Investigative, (c) Artistic, (d) Social, (e) Enterprising, and (f) Conventional; these six types also describe the work environments of different

occupations (Holland, 1973; Spokane, Luchetta, & Richwine, 2002). From the perspective of this theory, individuals strive to find an occupation that has an environment type that is congruent with one's personality type (i.e. a Realistic person will seek Realistic work environments; Holland, 1997). This theory was applicable to the present study because the program from which the researcher drew participants used of a career development intervention targeting participants with a particular career interest. Holland (1959) noted, "Persons with more information about occupational environments make more adequate choices than do persons with less information" (pp. 40-41). This sentiment would also be relevant in regard to students' choice to persist in an academic major; moreover, one goal of career development interventions is often to increase individuals' understanding of various career options. Within the present study, the participants all had expressed an interest in STEM but have varying levels of commitment to STEM fields as a possible career option. Despite more recent advancements with Holland's (1997) theory to include identity as a factor in the person-environment fit equation, researchers agree that additional factors (e.g. gender and self efficacy) can also influence one's desire to pursue a particular career field (Gottfredson & Johnstun, 2009; Spokane et al., 2002).

Social Cognitive Career Theory

Social Cognitive Career Theory (SCCT; Brown & Lent, 1996; Lent, 2005; Lent & Brown, 2002) incorporates self-efficacy beliefs, outcome expectations, interests, action, and performance into the career development process. Lent, Brown, & Hackett (2002) incorporated elements of other vocational psychology theories, while keeping a constructivist view that

individuals have influence of their own career development. Within the SCCT framework, self-efficacy beliefs can influence one's outcome expectations and, ultimately, the outcome of the process. For individuals within STEM, these self-efficacy beliefs may relate to the lack of representation within the field; if one cannot visualize someone like them choosing to enter a particular field, that person will likely not be able to visualize someone like them being successful in that field (Niles & Harris-Bowslbey, 2009). Similarly, SCCT might suggest a relationship between individuals' beliefs about their math ability and their actual performance in math and a relationship between individuals' actual performance in math and their beliefs about being successful in STEM. Researchers have studied STEM retention within the context of SCCT, and self-efficacy beliefs were a significant predictor of retention, particularly when academic performance and demographics were factored into the model (Lee, Flores, Navarro, & Kangui-Munoz, 2015; Lent, Lopez, Lopez, & Sheu, 2008). However, these models did not include any predictors related to career readiness or career planning intervention participation.

Cognitive Information Processing

The Cognitive Information Processing (CIP) Approach (Peterson, Sampson, Lenz, & Reardon, 2002; Peterson, Sampson, & Reardon, 1991; Sampson, Lenz, Reardon, Peterson, 1999; Sampson, Peterson, Lenz, Reardon, & Lenz, 1996a) was important to this study because the career development course discussed in this study was designed using the CIP Approach and because the researcher included CIP constructs within the independent variables of the study. The theoretical framework of the CIP Approach is twofold, with a focus on both the content of

the career development process (i.e. self knowledge, knowledge of the world of work, and decision-making skills) and the process of career development (i.e. the steps through which one goes when making a career decision). In CIP, dysfunctional thinking can negatively impact one's readiness to make decisions about careers (Jaensch, Hirschi, & Freund, 2015). The Career Thoughts Inventory (CTI) is an instrument that can help identify the type of negative career thinking that is affecting an individual, including Decision Making Confusion, Commitment Anxiety, and External Conflict (Sampson et al., 1996a; Sampson, Peterson, Lenz, Reardon, & Saunders, 1996b). Career development interventions and programming within the CIP framework fairly consistently result in reductions in negative career thinking (Dipeolu, Snitecki, Storlie, & Hargrave, 2013; Meyer & Shippen, 2016; Prescod, Daire, Young, Dagley, & Georgiopoulos, In press; Sampson et al., 1996a). More specifically, researchers have demonstrated a relationship between participating in career planning courses framed around CIP, such as the one used within the present research, and positive outcomes for undergraduate students (Folsom, Peterson, Reardon, & Mann, 2004; Osborn, Howard, & Leierer, 2007; Reardon, Melvin, McClain, Peterson, & Bowman, 2015)

Population Disparities within STEM

Disparities exist for females within both the STEM workforce and STEM degree programs (National Math and Science Initiative [NMSI], 2016). In the United States, females account for approximately half of the total workforce but only about 23 percent of the STEM workforce. Females are grossly underrepresented in some fields like engineering, but have

reached or surpassed gender parity in other fields like biological sciences; moreover, females are now overrepresented in science-related fields not considered a part of STEM, including psychology and non-diagnosing health practitioner fields like nursing (ACT, 2014, NSF National Center for Science and Engineering Statistics [NCSES], 2015). With regard to undergraduate retention, the presence of gender stereotyping and stereotype threat (i.e. group-based performance anxiety) was a significant predictor of attrition from STEM majors for females (Beasley & Fischer, 2012; Cundiff, Vescio, Loken, & Lo, 2013). Gayles and Ampaw (2014) found that females overall were less likely to be retained in STEM, especially when math remediation was necessary.

Whereas marginalized ethnic minority groups (i.e. Black/African American and Hispanic) have made gains in some STEM fields (e.g. computer science, biological science), they are still underrepresented within general STEM employment and degree attainment (Palmer et al., 2011). Foltz, Gannon, and Kirschmann (2014) found that connections with STEM faculty mentors and undergraduate peers who are also from an underrepresented ethnic minority group was a protective factor for STEM retention; however, because of underrepresentation, individuals find challenges in attain mentors and peer groups within these groups. Researchers identified an interaction between gender and ethnicity with regard to STEM major selection retention, as females from underrepresented ethnic groups tended to have better outcomes than their male counterparts (Beasley & Fischer, 2012; Cundiff et al., 2013; Gayles & Ampaw, 2014; Riegle-Crumb & King, 2010). However, findings were inconsistent and, in some cases,

contradictory as to which subgroups had better or worse outcomes, particularly for male students from across underrepresented ethnic groups.

Math Ability and STEM

In prior studies, researchers identified math ability as a significant factor in STEM outcomes for undergraduates, including performance in class, overall grade point averages, and retention (CollegeBoard, 2012; Crisp et al., 2009; Le, Robbins, & Westrick, 2014; Rohr, 2012). Achieving higher SAT Math scores and taking higher level math courses in high school both translated into a higher likelihood of completing a STEM major (Chen, 2013; CollegeBoard, 2012). However, numerous research studies over several decades have highlighted potential test bias with the SAT based on race, noting that lower mean family income and decreased access to SAT preparation courses contribute to Black students having lower mean SAT scores than their White counterparts (Dixon-Román, Everson, & McArdle, 2013; Lawlor, Richman, & Richman, 1997; Temp, 1971; Toldson & McGee, 2014). As a result, CollegeBoard revised the SAT in 2016 to address these concerns, and many universities have changed admissions and decision-making polices regarding the use of college entrance exams (CollegeBoard, 2017; Toldson & McGee, 2014). Nevertheless, the SAT remains one of the most commonly used college entrance exams (CollegeBoard, 2017). Beyond the issues documented with the SAT, researchers have also found that increased math anxiety and the need for math remediation are both correlated with a decreased chance of completing a STEM degree, particularly for female students (Cundiff et al., 2013; Nosek & Smyth, 2011).

Career Planning Coursework and STEM

Students who participate in a career planning course are more likely to be retained in their major until graduation (Folsom, Peterson, Reardon, & Mann, 2004; Parks, Rich, & Getch, 2012; Reardon, Melvin, McClain, Peterson, & Bowman, 2015). Whereas career-related coursework within STEM programming often focuses on students with declared STEM majors rather than undeclared students, researchers found that these programs did yield positive results (Freeman, 2012; Gentile et al., 2012). STEM professionals, rather than career development professionals, taught two particular STEM-related courses found in the literature; as such, these courses were more focused on providing information to students about various STEM majors, rather than using a career development process to help students select a potential major (Freeman, 2012; Gentile et al., 2012). Nevertheless, these courses resulted in increased identification with a STEM major, increased participation in undergraduate research, and increased likelihood of retention through the second year of college. In another study, undeclared students participating in a STEM-focused career planning course saw a larger decrease in negative career thinking than declared STEM majors in a seminar class without a career development focus (Prescod et al., In press). Similarly, in a pilot study to this dissertation, the researcher found similar findings as Prescod et al. (In press); in addition, after adjusting for covariates, the undeclared students in the STEM-focused career planning course had lower scores on a measure of negative career thinking than the declared students in the seminar course at the end of their first semester of college.

A second pilot analysis informed the present study more (Belser, Prescod, Daire, Dagley, & Young, 2017). The results of this study indicated that participation in a career development course, initial major, and CTI change scores could accurately predict which students would be retained in a STEM major from their first year to their second year. However, the final model produced in the study was only accurate in predicting non-retained students with only about 43 percent of cases and had a fair overall model fit. As the researchers did not include demographic or math-related variables in the model, considering these variables in future research may yield a more accurate model.

Research Hypotheses

Based on the existing literature, it is clear that researchers only minimally investigated career development factors as predictors of undergraduate retention within STEM majors (Belser et al., 2017; Lee et al., 2015; Lent et al., 2008). As such, a research gap exists with regard to how career-related variables, such as participation in career development programming and measures of career readiness, fit into predictive models along with demographic variables and math aptitude scores. As such, in this study, the researcher used binary logistic regression to determine the degree to which demographic variables (gender, ethnicity, and initial major), math ability scores (SAT Math scores and Math Placement Test scores), and career development factors (STEM Course Participation and Career Thoughts Inventory [CTI] change scores) could

predict undergraduate retention in STEM majors during the first two years of college. To answer the aforementioned questions, the researcher tested the following six hypotheses:

> Null Hypothesis 1: First-year to second-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, STEM Course Participation (Career Planning vs. STEM Seminar), and CTI change scores.

> Null Hypothesis 2: First-year to second-year undergraduate retention in STEM majors for students participating in a STEM-focused Career Planning Course cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

> Null Hypothesis 3: First-year to second-year undergraduate retention in STEM majors for students participating in a STEM Seminar Course (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

> Null Hypothesis 4: First-year to third-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test

scores, SAT Math scores, STEM Course Participation (Career Planning vs. STEM Seminar), and CTI change scores.

Null Hypothesis 5: First-year to third-year undergraduate retention in STEM majors for students participating in a STEM-focused Career Planning Course cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 6: First-year to third-year undergraduate retention in STEM majors for students participating in a STEM Seminar Course (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

With this study, the researcher hoped to contribute to the current literature related to STEM initiatives with undergraduates and to lay groundwork for future research with career development and STEM. Additionally, findings from the present study have implications for career development personnel within higher education institutions regarding programming for undergraduates interested in or majoring in a STEM discipline. This research also helps solidify the role of counselor educators as career development content specialists within STEM initiatives.

Professional Significance

The current study has implications for research on STEM initiatives. First, although prior research has investigated the influence on demographic variables and math ability on retention in STEM (ACT, 2014; Beasley & Fischer, 2012; Cundiff et al., 2013; Gayles & Ampaw, 2014; NMSI, 2016; Palmer et al., 2011; Riegle-Crumb & King, 2010), career related variables have not been investigated with the same degree (Belser et al., 2017; Le, Robbins, & Westrick, 2014; Lent et al., 2016; Prescod et al., In press; Porter & Umbach, 2006). In addition, the existing studies that have examined career development as a predictor of retention in STEM have primarily focused on students who have a declared STEM major rather than initially undeclared students. The current study provided insight on how career development related variables compare to previously studied variables with regard to predicting retention in STEM majors. Moreover, the inclusion of both declared and undeclared students provided an avenue to explore how a predictive model might look different for each group. Findings from the study serve to fill gaps in the current literature and provide a foundation for future research in this area.

As noted, colleges and universities are investing millions dollars from federal agencies and private organizations to address the STEM crisis, with lots of money being spent on students who still end up leaving their STEM major (Carnevale et al., 2011). For higher education professionals and career counselors tasked with creating STEM initiatives, identifying which variables are most aligned with retention or attrition can assist with program development. Such information could help these professionals begin to provide general services in the areas associated with retention and then targeted interventions for those identified as being at risk for

dropping out of a STEM major. This research also has implications for potential differences in the variables associated with retention for declared students and undeclared students.

The present study also has significance for counselor education. Counseling literature focused on STEM initiatives has primarily been discussed in relation to K-12 settings with school counselors and largely has not been empirically based. However, the COMPASS Program is a unique endeavor in which individuals from counselor education brought career development expertise to a higher education STEM initiative. This research opens doors for other interdisciplinary collaborations, in which individuals from counseling and counselor education can provide critical knowledge and expertise in the area of career development that can impact STEM retention. These partnerships equate to research initiatives and external funding. In a review of nearly 3,000 projects funded by the Directorate for Education and Human Resources of the National Science Foundation since the 1970s, the researcher found five projects whose research would serve to advance the science of career development within the context of STEM (NSF, 2017). Of these programs, four were framed around career development theory, and three involved professionals from counselor education or counseling psychology. Moreover, two involved a career development intervention for students who had not yet decided to pursue a STEM career; one of these was the COMPASS program and one was a program for females aged 10 to 14. As such, the findings of the present study can serve as a foundation for future evidence-based outcome research involving STEM career initiatives.

Methodology

For the current study, the researcher used data collected as part of the UCF COMPASS Program, which focused on recruiting and capturing undecided undergraduates into STEM majors with the long-term goal of increasing retention in STEM majors. Because the study was part of an active research project, approval from the UCF Institutional Review Board (IRB) was already in place. The following sections outline the research design, sampling, data collection and instrumentation procedures, as well as the data analysis that the researcher used.

Design

For the study, the researcher used a quasi-experimental design with non-equivalent comparison groups (Campbell & Stanley, 1963; Gall, Gall, & Borg, 2007). The participants were selected into the UCF COMPASS Program using purposive criterion sampling, rather than random assignment. The research hypotheses explored whether a set of identified variables could predict retention or attrition in STEM majors across multiple years of college. In order to analyze these potential predictors within the context of the binary outcome (i.e. retention or attrition), the researcher tested the first three hypotheses regarding first-to-second year retention using a dichotomous dependent variable (coded as Retained in STEM or Not retained in STEM) and tested the last three hypotheses regarding first-to-third year retention using a dichotomous dependent variable (coded as Retained in STEM or Not retained in STEM). The researcher elected to analyze the data using binary logistic regression. Methodologists commonly recommend this procedure when the dependent variable is categorical, when independent

variables data are not normally distributed, and when the regression model will include both categorical and continuous variables as predictors (Agresti, 2013; Hosmer, Lemeshow, & Sturdivant, 2013; Tabachnick & Fidell, 2013. Although predictors can be selected for the model using several procedures, this study used purposeful selection of predictors based on a review of the literature (Hosmer et al., 2013).

Population and Sample

The population for this study included STEM-interested undergraduates who were members of a STEM recruitment and retention program. The researcher drew the sample from the UCF COMPASS Program, which is a federally funded initiative that seeks to recruit and capture undecided STEM-interested students into STEM majors (National Science Foundation STEP 1B: No. 1161228). Participants expressed an interest in STEM majors based on their self-selection into the STEM-focused program, but they had not yet committed to a particular major at the time they applied. Criteria for selection into the program included (a) being a first time in college student, (b) having an SAT Math score between 550 and 800, (c) having an undeclared major status at the time of application, and (d) having a potential interest in pursuing a STEM major. In addition to the two STEM-specific studies referenced throughout this dissertation, the COMPASS Program also connects students to a peer mentor, hosts an undergraduate research experience, and provides math support through tutoring and designated course sections. For purposes of defining STEM, the COMPASS program considers the following majors as STEM majors at UCF: Aerospace engineering, Biology, Biomedical Sciences, Biotechnology,

Chemistry, Engineering (all branches), Computer Science, Forensic Science, Mathematics, Photonics, Physics, and Statistics. All participants joined the COMPASS Program between Fall 2012 through Fall 2015 semesters. Participants with an undeclared major took a STEM-focused career planning course in their first semester, whereas initially undecided participants who declared a STEM major between the time of admission to the program and the first day of class took a STEM Seminar class that did not have a career planning focus. The researcher defined these two courses later in this chapter and in subsequent chapters. Participants received and signed an informed consent document indicating their rights as subjects of a research study.

Data Collection

The University's Institutional Knowledge Management (IKM) Office provided most of the data that the researcher used within this study, including demographic information (gender and ethnicity), academic data (SAT Math scores and Math Placement Test scores), major related variables, and retention data. As such, a demographic questionnaire was not needed. The IKM Office provided these data in comma-separated values (CSV) files, which were transferred to one Statistical Package for Social Sciences (SPSS) file. Participants completed the Career Thoughts Inventory during the first and last week of their first semester in either the STEM-focused Career Planning course or the STEM Seminar course. The researcher and a team of trained research assistants then added the scores to the SPSS file.

Instruments and Instrument Data

The researcher utilized results from three instruments: (a) the Career Thoughts Inventory (Sampson, Peterson, Lenz, Reardon, & Saunders, 1996a; Sampson, Peterson, Lenz, Reardon, & Saunders, 1996b); (b) the SAT Mathematics subtest (CollegeBoard, 2012; 2016); (c) the UCF Math Placement Test: Algebra subtest (University of Central Florida, 2016). Participants took the SAT prior to applying for admission to the University and the program. Next, participants completed the Math Placement Test after being admitted to the university to determine their math course registration for their first semester. Finally, participants completed the Career Thoughts Inventory as part of COMPASS course programming during the first week of their first semester of classes.

The Career Thoughts Inventory (CTI) measures negative career thinking by asking participants to indicate their level of agreement with 48 statements about the career selection process (Sampson et al., 1996a; Sampson et al., 1996b). The measure provides a total score and three subscale scores: (a) Decision Making Confusion; (b) Commitment Anxiety; and (c) External Conflict. Each subscale provides more specific insight into the source of one's negative career thinking. Completing the CTI yields a raw score and a *T*-score for the CTI Total and each of the subscales. *T*-scores higher than 50 are indicative of problematic career thinking in at least one area. Sampson et al. (1996a) provided alpha coefficients for internal consistency that ranged from .93 to .97 for the CTI Total and from .74 to .94 for the three subscales. This study utilized change scores calculated by subtracting the pre-test scores from the post-test scores for the CTI Total and the three subscales. Using the Reliability Analysis procedure in SPSS, the researcher

found alpha coefficients for the CTI pretest of .95 for the CTI Total score, .87 for the DMC subscale, .88 for the CA subscale, and .71 for the EC subscale; similarly, the researcher found alpha coefficients for the CTI posttest of .96 for the CTI Total, .92 for the DMC subscale, .89 for the CA subscale, and .83 for the EC subscale. These measures of internal consistency were within the same ranges as the coefficients of Sampson et al. (1996a), with the exception of the EC subscale that was .03 lower than the norm group but still within the acceptable range (DeVellis, 2012; Kline, 2000).

The SAT is a test commonly used by colleges and universities for the purpose of making admissions decisions (CollegeBoard, 2016). The test includes four subtests: (a) Essay, (b) Critical Reading, (c) Writing, and (d) Mathematics; the overall score can range from 600 to 2400 and subtest scores (except the Essay) range from 200 to 800. This study utilized only scores from the SAT Math subtest. This subtest is timed and includes 54 items related to math fluency, conceptual understanding, and applications (CollegeBoard, 2016). Ewing et al. (2005) reported an alpha coefficient of .92 for overall internal consistency, with coefficients ranging from .68 to .81 for the four identified skill areas that are part of the SAT Math test. Because the Institutional Knowledge Management Office only provided the scale scores without individual item responses, the researcher could not run reliability statistics on the SAT for the data set.

The UCF Math Placement Test is a university-made assessment that is used to determine the math course in which students should start their math sequence at the university. It is a timed assessment with three content areas: (a) algebra, (b) trigonometry, and (c) pre-calculus (UCF, 2016). Students begin with the algebra section, and if they complete this test with 70 percent

accuracy, they are invited to take the other two sections of the test. The University had not yet made psychometric properties for the Math Placement Test available at the time of this dissertation. Because every student taking the Math Placement Test completes the Algebra subtest but may not take the other subtests, the researcher opted to use only the Algebra subtest scores for this study. Additionally, the University only recommended the Math Placement Test for incoming students at the beginning of the data collection process but made the test a requirement partway through the data collection process; as such, the researcher expected missing data for participants who joined the COMPASS program before the Math Placement test became a requirement.

Data Analyses

Within the present study, the researcher examined six hypotheses using binary logistic regression to determine which of the pre-selected independent variables can predict group membership in a binary categorical dependent variable (Agresti, 2013; Hosmer et al., 2013; Tabachnick & Fidell, 2013). After compiling data into one data file, the researcher conducted preliminary analyses to identify univariate and multivariate outliers and to evaluate missing data, resulting in the removal of 16 outliers and data imputation using the Expectation Maximization The final set of preliminary analyses involved checking the data for possible violations of the assumptions for logistic regression, including the following: (a) checking the ratio of cases to predictor variables, (b) verifying a linear relationship between the logit transform of the dependent variable and continuous predictors, (c) checking for multicollinearity, and (d) examining potential outliers in the solution (Tabachnick & Fidell, 2013). To test the first three

hypotheses, the researcher used Year Two STEM Retention as the outcome variable (i.e. retention from first year to second year), and to test hypotheses four through six, the researcher used Year Three STEM Retention as the outcome variable (i.e. retention from first year to third year). Testing hypotheses two and five only required the use of students from the STEM-focused Career Planning course, whereas testing hypotheses three and six only required the use of students from the STEM Seminar class.

Definitions of Terms

This section includes operational definitions for common terms or phrases used within this study.

Career Development: defined as the process by which individuals make decisions about careers. An individual's career development process may occur naturally or may involve interventions from a career development professional (Niles & Harris-Bowlsbey, 2009). The researcher framed this study around four theories of career development, which were discussed in a prior section.

Career Development Intervention: defined as a treatment or initiative provided by a career development professional to aid in an individual's career development process, including making informed career decisions (Niles & Harris-Bowlsbey, 2009). The STEM-focused Career Planning class discussed within this study is one example of a career development intervention.

Career Thoughts: defined as thoughts developed by an individual about career problems and career decision making based on one's assumptions, biases, beliefs, and intentions (Peterson et al., 1991).

First-year student: defined as an undergraduate student who is enrolling in a university for the first time. This term is used in place of the term Freshman, as some students enter the university as first-year students with enough credit from dual enrollment, Advanced Placement courses, and other means to have a higher classification.

STEM Retention: defined as the status of remaining declared in a STEM major to a specific time point, such as the end of an academic year or graduation. This study will utilize two time points. First-year STEM retention refers to one being retained in STEM at the completion of their first academic year. Second-year STEM retention refers to one being retained in STEM at the completion of their second academic year.

STEM-Focused Career Planning course: defined as a 16-week academic course taken at a university to enhance an individual's career development process or to help an individual select an appropriate major or career. This course involves career assessment, career exploration, and career decision-making. In the first phase of the course, students take a battery of career assessments to aid in understanding interests, values, skills, personality type, decision-making processes, and more. In the second phase, professionals from STEM industries and academia present their career fields to the students in the class and students also participate in visits to

STEM research labs; within the class, students reflect on their experiences with these activities and whether these STEM fields would be a good fit for them. In the third and final phase, students complete a career action plan and a research paper about a career field of choice; the goal of this phase is for them to make a decision about their college major.

STEM Seminar class: defined as a one credit hour 16-week academic course taken at a university to support individuals with declared STEM majors who are a part of the COMPASS program. In this course, students hear from guest speakers representing STEM fields, learn about undergraduate research and internship opportunities, participate in STEM lab visits, and engage in a service learning activity. Students in this course take the Career Thoughts Inventory at the beginning and end of the course; the assessment results are explained to the students but are not used within the course to aid in confirmation of students' major choice. On numerous occasions throughout the semester, students participate in review sessions for their mathematics courses in lieu of a regular class meeting; as students in the program have required study hours, students can substitute these math review classes in lieu of their required study hours.

Limitations

The current study had a number of limitations. First, the study did not include a control group. Both the Career Planning group and the STEM Seminar group received an intervention as part of the program, with the STEM-focused Career Planning Course utilizing a more systematic career planning approach; the lack of a true control group limits the causal inferences that may have been drawn regarding the career development interventions used. Maturation and history may have been natural threats to internal validity, and the lack of a control group

prevented the researcher from discerning what differences may be attributed to maturation, rather than between group differences. The data utilized in this study only represented one university and one STEM program, so the findings may only be generalizable to similar programs. Similarly, the variables used within the study were not comprehensive; therefore, additional factors contributing to STEM retention may exist. Because of the sample size, some subgroups within the ethnicity variable violated the recommended number of cases in each of the possible retention outcomes (Field, 2009; Peduzzi et al., 1996). As such, readers should view coefficients from these variables with caution. Also, the researcher is also the instructor for the Career Planning Course and a Graduate Assistant for the COMPASS Program, which may result in participants acting differently than they would in a career planning course not attached to a research study.

Summary

Currently, low undergraduate retention rates for STEM disciplines help perpetuate the STEM Crisis. Just as troubling, these rates contribute to a cycle of underrepresentation for women and certain ethnic minority groups in STEM disciplines. Colleges and universities have sought to address these disparities through externally funded STEM initiatives, but prior research on such endeavors has primarily focused on examining demographic variables and math-related variables with regard to retention in STEM. Researchers have largely overlooked career development related variables, leading to a lack of understanding of their impact on STEM retention.

In the present study, the researcher sought to explore a critical gap in the literature related to variables that may predict undergraduate retention in STEM, particularly career-related variables. This study gave particular attention to understanding how demographic variables, math ability, career development participation, and career readiness could uniquely predict whether undergraduates are more likely to be retained in a STEM major or not during their first two years of college. The findings of this study have implications for STEM-interested researchers, career and higher education practitioners, and counselor educators.

CHAPTER II: LITERATURE REVIEW

The National Science Foundation (NSF, 2013) and the National Academy of Sciences (NAS, 2011) both indicated that the number of qualified workers to fill jobs in science, technology, engineering, and math (STEM) fields lags behind rates of growth and advancements within these fields. In 2011, researchers projected that job growth within STEM fields would grow by 17 percent through 2018 (Carnevale, Smith, & Melton, 2011). However, because of identified job growth in these fields, increases in retirements within the Baby Boomer generation, and low completion of STEM degrees, researchers predicted that the United States will be short as many as three million high skilled STEM workers by 2018 (Carnevale et al., 2011; National Math & Science Initiative [NMSI], 2016). These issues, commonly referred to in aggregate as the "STEM Crisis," have also sparked debate about the United States' ability to remain competitive in an increasingly more global economy (Chen, 2013; NSF, 2013; NAS, 2011).

The STEM Crisis

Existing literature presents a varied perspective on the extent to which the STEM Crisis has impacted employment across STEM disciplines (Carnevale et al., 2011; National Science Board [NSB], 2015; Xue & Larson, 2015). Rather than arguing that there are across-the-board shortages in STEM fields, Xue and Larson (2015) posited that shortages do exist and that they

likely vary across STEM disciplines, degree levels of workers, and geographic locations (e.g. the demand for degreed petroleum engineers will likely be different in Texas than in Vermont). The discrepancy between the availability of STEM jobs in industry and academia is another commonly cited example that highlights that both a STEM crisis argument and a STEM surplus argument can be valid. Whereas there are shortages within some industry-based fields (e.g. computer/technology fields and Department of Defense engineering jobs) because of increased retirements and creation of new jobs, academic positions have not seen the same increase, resulting in these opportunities becoming more competitive (NSB, 2015). Carnevale et al. (2011) added that candidates qualified for STEM positions are graduating from college and taking positions in non-STEM jobs that are seeking candidates with similar qualifications. Another important aspect of the disagreement over whether there is a STEM crisis or a STEM surplus is that some researchers have looked just at raw numbers of STEM graduates compared to STEM positions, which leads to a conclusion that there is a surplus; however, these numbers must also be broken down based on the number of *qualified* workers for existing and new positions, disparities across gender and racial/ethnic groups, and interacting effects of these factors (NSB, 2015).

Chen (2013) reported that less than 30 percent of students with a bachelor's degree had chosen a STEM major; additionally, nearly half of these students who entered a four-year institution with a declared STEM major changed to a non-STEM major prior to graduation or left college. Of these students who exited their STEM degree program, nearly half left college altogether and half changed their majors to something outside of STEM. Within Chen's (2013)

sample, students who left their STEM majors attempted an average of 11.4 credit hours of STEM coursework. Retention rates vary significantly around the country, with some institutions reporting retention rates around 30 percent (Koenig, Schen, Edwards, & Bao, 2012). As a result of these high rates of attrition within STEM, many post-secondary institutions have developed programs targeting retention in undergraduate STEM disciplines (Bouwma-Gearhart, Perry, & Presley, 2014; Defraine, Williams, & Ceci, 2014; Schneider, Bickel, & Morrison-Shetlar, 2015). In addition to aggregate retention in STEM, many of these programs included initiatives to address disparities across gender and ethnic groups (Chen, 2013; Palmer, Maramba, & Dancy, 2011). The National Science Board (NSB, 2016) indicated that recent spikes in the number of STEM graduates relate highly to the number of international students coming to the United States to pursue STEM degrees; this influx of international students completing STEM degrees in the United States is problematic in cases in which the student does not remain in the United States after graduation, as these cases increase the retention and graduation rates without adding candidates to the U.S. STEM workforce.

Billions of dollars are spent each year on STEM initiatives at the K-12 and postsecondary levels, with most coming from the federal government through grants from the National Science Foundation, the Department of Defense, and the Department of Education (Carnevale et al., 2011). The 2016 federal budget appropriated more than $1 billion to STEM initiatives through the National Science Foundation and Department of Education alone (US House of Representatives, 2016). As previously stated, the nearly five million Baby Boomers expected to retire from STEM jobs and the disparities in some underrepresented populations within STEM

(e.g. women, people of color) both are cause for concern for the STEM labor market in the United States (Carnevale et al., 2011). Currently, the STEM labor market is underutilizing individuals from demographic groups that comprise nearly half of the U.S. population (i.e. women and ethnic minorities) and instead is filling in gaps in STEM with foreign-born workers (Carnevale et al., 2011).

The purpose of this review was to examine empirical and theoretical literature related to STEM declaration and academic persistence in STEM majors. For the purposes of the review, the researcher defined STEM declaration as the process of selecting a major within a science, technology, engineering, or math field; STEM declaration can entail changing a major from a non-STEM major to a STEM major or moving from and undeclared major to a declared STEM major. Academic persistence, or retention, was defined as the process of remaining within a STEM major until graduation and obtaining a STEM degree. The researcher framed this literature review around three primary constructs as they pertain to STEM retention and degree attainment: (a) demographic variables, (b) math ability, and (c) career development factors. Demographic variables include gender, ethnicity, and the interaction between the two, whereas math ability refers to students' performance on standardized math assessments; this section also examines the effect of stereotyping on math ability. The career development section considers several career development theories, previous predictive models related career initiatives within STEM, and STEM-focused career planning classes.

Gender Disparities in STEM

Gender disparities exist both within the STEM workforce and in STEM degree programs (NMSI, 2016). Whereas women make up nearly 48 percent of workers in all occupations, they only account for 23 percent of workers in STEM fields. Equally startling, men aged 25 and older hold 87 percent of engineering bachelor's degrees, with white men accounting for approximately one half of the science and engineering workforce (NSF National Center for Science and Engineering Statistics [NCSES], 2015). Science-interested females are more likely to be interested in and are overrepresented in non-diagnosing health practitioner fields (e.g. nursing, dental hygienist) and psychology (ACT, 2014; NSF, 2015); however, these are not included on the NSF STEM Classification of Instructional Programs Crosswalk (NSF, 2016). Within engineering fields, females are more likely to enter chemical, materials, industrial, or civil engineering programs, rather than aerospace, mechanical, or electrical engineering programs (NCSES, 2015). The fields of computer science, mathematics, and physics have seen either stagnation or decline in female participation the undergraduate level (NCSES, 2015).

Mansfield, Welton, & Grogan (2014) established through a qualitative policy analysis that gender disparities within STEM fields has been a topic of public discourse and policy discussions for numerous years; however, they concluded that stakeholders have not adequately addressed gender-related barriers to success in STEM at the appropriate level (i.e. K-12 education) in order to yield results at the undergraduate level. Riegle-Crumb, Grodsky, and Muller (2012) analyzed data from three national education data sets at three different time points over a 22-year span; they found males took calculus and physics courses at significantly higher

rates at all three time points. These data likely partially explain why undergraduate females were more likely to change from a STEM major to a non-STEM major, as non-STEM majors are less likely to require higher-level math courses (Chen, 2013).

Gender stereotypes have also played a role in the disparities within STEM. Beasley and Fischer (2012) explored the role of stereotype threat (i.e. group-based performance anxiety) in students' decision to declare a STEM major; in their analysis, females were overall less likely to declare a STEM major (OR = .59, $p < .001$) and at significantly lower rates for Black (OR = .87, $p < .01$), Hispanic (OR = .79, $p < .001$), Asian (OR = .51, $p < .001$), and White (OR = .50, $p < .001$) females. The researchers noted that females were overall more likely to leave their STEM major, which they hypothesized was due to experiences of stereotype threat; however, they did not report the odds ratio. When the researchers examined group anxiety (their measure of stereotype threat), the odds of leaving a STEM major were higher for Black females (OR = .80) and Hispanic females (OR = .57) than their male counterparts; White females (OR = .61) actually had lower odds of leaving their STEM majors than White males (OR = .65), albeit a small difference. The authors did not report a standardized measure of effect size. This particular study was among the first to examine the effect of stereotype threat on persistence within a major, rather than just in short-term testing situations.

Litzler, Samuelson, & Lorah (2014) found different results in a sample of over 7,800 engineering students at 21 post-secondary institutions. Using multilevel linear regression, the authors sought to compare levels of confidence in STEM across gender and racial groups, with White males as the reference category. In their first model that did not include covariates, all

demographic subgroups had significantly or non-significantly lower STEM confidence scores. The STEM confidence scores were significantly lower for Asian males (b = -.30, $p < .001$), Hawaiian/Pacific Islander males (b = -.57, $p < .05$), White females (b = -.18, $p < .001$), African American females (b = -.34, $p < .001$), Hispanic females (b = -.23, $p < .001$), and Asian females (b = -.37, $p < .001$); the other five subgroups (African American males, Native American males, Hispanic males, Native American females, and Hawaiian/Pacific Islander females) had lower STEM confidence scores than White males, but the differences were non-significant. Their second model included covariates related to the university environment (e.g. good professors, student community). After adjusting for covariates, only White females continued to have significantly lower confidence scores (b = .07, $p < .01$). The researchers acknowledged that their sample was skewed by overrepresentation of females compared to the actual STEM population; however, they did not address that non-White males and females accounted for a combined 28.5 percent of the total sample used in the analysis, with the Hawaiian/Pacific Islander and Native American subgroups combined accounting for less than 2 percent of the total sample. The first model without covariates explained approximately 2 percent of the variance in STEM outcomes, whereas the second model with covariates explained approximately 37 percent of the variance in STEM outcomes.

Several models have been used to predict STEM participation and retention with regard to gender. Females were less likely to be retained in STEM, as were racial/ethnic minorities, in two identified studies (Cundiff, Vescio, Loken, & Lo, 2013; Gayles & Ampaw, 2014). Cundiff et al. (2013) explored the effect of gender stereotypes on individuals' intent to persist in science.

Their sample included approximately 1,800 undergraduate students from introductory biology, chemistry, and physics courses at one university. For females, stronger gender stereotypes in science predicted weaker science identification and a weaker desire to pursue a science career (Path $a = -0.28$, $p < .01$, $R^2 = .34$). In contrast for males, stronger gender stereotypes in science predicted stronger science identification and an increased desire to pursue a science career (Path $a = 0.18$, $p < .01$, $R^2 = .20$). The authors noted that their sample did not include STEM-interested students without a declared major and suggested that subsequent research should investigate the effect of gender stereotyping on major selection, rather than desire to continue in a STEM major.

Gayles and Ampaw (2014) examined the relationship between the college experience and STEM degree attainment based on gender. Using a subset of a national dataset ($n = 1{,}488$), the researchers ran a binary logistic regression to analyze predictors of STEM degree completion. Compared to the entire sample, female students were overall less likely to complete a STEM degree than male students ($OR = 0.84$, $SE = 0.01$, $p < .01$). Hispanic females ($OR = 0.40$, $SE = 0.02$, $p < .01$) and Black females ($OR = 0.72$, $SE = 0.03$, $p < .01$) were significantly less likely to complete a STEM degree than their male counterparts. Another interesting finding was that female students who did not need math remediation ($OR = 13.9$, $SE = 1.15$, $p < .01$) were significantly more likely to complete a STEM degree than their male counterparts ($OR = 0.38$, $SE = 0.02$, $p < .01$). These studies provide a rationale for further inclusion of gender as a variable in predictive models. The authors reported odds ratios as measures of effect size.

Race/Ethnicity Disparities within STEM

Similar to gender, there are also disparities in STEM degree attainment and STEM employment across racial and ethnic groups, primarily with people of color (NSF, 2013; Palmer et al., 2011). Underrepresented minority groups have made gains in degree attainment within psychology, social sciences, computer sciences, and biological sciences, but have had stagnant or decreasing participation within engineering, physical sciences, and mathematics (NSF, 2015). Chen (2013) reported that Black students were more likely to leave their STEM major either by dropping out of college or by changing to a non-STEM major. In contrast, Foltz, Gannon, & Kirschmann (2014) found through qualitative inquiry that minority STEM students identified college-going expectations from the family-of-origin, close connections with STEM faculty members, integration with overall campus life, a sense of community with other minority students in similar programs as protective factors that support retention in STEM majors. However, minority underrepresentation in STEM for both students and faculty creates inherent difficulties in fostering these relationships. In a longitudinal analysis of data from the Department of Education, the NSF NCSES (2015a) found that ethnic minority males and females separately attained STEM bachelor's degrees at approximately the same rate as the overall aggregate (males and females combined) for each racial/ethnic group; the only exception was with Black or African American students, where female students were awarded STEM degrees at a higher rate than males.

Riegle-Crumb and King (2010) encouraged researchers to examine the intersectionality of race/ethnicity with gender within STEM fields. In their analysis of a national education data set, they found that higher percentages of Black (35.5 percent) and Hispanic (33.9 percent) males chose physical science and engineering majors than their white male counterparts (30.7 percent), with a somewhat similar ratio for Black (15.9 percent) and Hispanic (12.7 percent) females compared to white females (13.1 percent). The researchers did note, however, that their sample only included students who entered four-year universities, which eliminated a disproportionate number of minority students from the sample.

As suggested by Riegle-Crumb and King (2010), many predictive models that examined demographics and academic persistence included both gender and ethnicity. The previous section highlighted a few predictive models that examined the effects of stereotypes and stereotype threat (Beasley and Fischer, 2012; Cundiff et al., 2013). Both studies showed a clear interaction between gender and race, particularly for non-White females. Models related to males-of-color showed mixed results, with some indicating a higher likelihood (Riegle-Crumb & King, 2010) and some showing a lower likelihood of obtaining a STEM degree (Cundiff et al., 2013; Gayles & Ampaw, 2014). Nevertheless, the obtained results warrant future models to include race as a predictor to investigate this variable further.

Mathematics & STEM

Higher Scholastic Aptitude Test (SAT) Math scores (a measure of subject area readiness) are correlated with higher grade point averages in first-year undergraduate math and science

classes (CollegeBoard, 2012). For example, students with an SAT Math score of 680 (representative of the 91st percentile) have a 75 percent probability of obtaining a 2.67 grade point average in first-year math and science courses and a 65 percent chance of obtaining a 3.0 grade point average in first-year math and science courses. The SAT is most often used in decisions related to university admission and can be used in conjunction with other assessments (e.g. math placement exams, Advanced Placement tests) to determine which math classes undergraduate students will start in when they enroll in post-secondary classes.

Despite the SAT being one of the most commonly used college entrance exams (CollegeBoard, 2017), numerous research studies over several decades have highlighted potential test bias with the SAT based on race, noting that lower mean family income and decreased access to SAT preparation courses has contributed to Black students having lower mean SAT scores than their White counterparts (Dixon-Román, Everson, & McArdle, 2013; Lawlor, Richman, & Richman, 1997; Temp, 1971; Toldson & McGee, 2014). As a result, CollegeBoard revised the SAT in 2016 to address these concerns, and many universities have changed admissions and decision-making polices regarding the use of college entrance exams (CollegeBoard, 2017; Toldson & McGee, 2014).

Three predictive models identified higher academic achievement and aptitude measured with the SAT as a predictor of academic success later in college (Crisp et al., 2009; Le, Robbins, & Westrick, 2014; Rohr, 2012). Mattern and Patterson (2013) examined the relationship between SAT scores and university retention to the second year. With a sample of over 215,000 students from 160 institutions, they found a positive association between SAT scores and second

year retention after accounting for gender, race, income, parents' education, and high school grade point average. The total sample had a mean SAT Math score of 572 (*SD* = 99.0); the retained students (*n* = 186,257) had a mean SAT Math score of 578 (*SD* = 98.0), whereas the non-retained students (*n* = 29,447) had a mean SAT Math score of 529 (*SD* = 95). Their primary analysis examined the SAT composite score rather than the Math subscore. The retention rate increased from 60 percent with the lowest composite score band (600-890) to 96 percent with the highest score band (2100-2400). The positive trend remained consistent when broken down by gender and ethnicity. The authors did not provide an *r* value for the correlation between SAT scores and retention or any measures of effect size; moreover, it must be noted that the research conducted in this study was supported by CollegeBoard, the creator of the SAT.

Chen (2013) reported that undergraduates who had taken higher-level math courses in high school (e.g. Pre-calculus and Calculus) left their declared STEM majors at a lower rate (12 percent) than students who had not taken higher level math courses in high school (41 percent). However, many students with high math potential choose majors outside of STEM, as evidenced by comparable SAT Math scores for STEM majors (e.g. Engineering, Biological Sciences, Mathematics, Computer Science) and non-STEM majors (e.g. foreign/classical languages, legal studies, literature) within one report (Carnevale et al., 2011). These findings provide evidence that higher math aptitude can help students be successful both in STEM and non-STEM fields, but that it provides a necessary boost to students who do intend to major in a STEM field.

As noted in the previous sections, researchers have connected math ability and math efficacy to gender and ethnicity. Nosek and Smyth (2011) found that females across the lifespan exhibited lower implicit warmth for math (M = 5.16, SD = 2.57, d = -.29, $p < .05$) than males (M = 5.93, SD = 2.41), lower explicit identification with math (M = -.25, SD = .75, d = -.27, $p < .05$) than males (M = -.03, SD = .76), and lower self-ascribed math ability (M = -.11, SD = .79, d = -.28, $p < .05$) than males (M = .13, SD = .76). These findings likely shed light on gender disparities within participation in higher-level math courses in high school and undergraduate retention in STEM majors. Similarly, Gayles & Ampaw (2014) noted that females who do not need math remediation in college have a significantly higher likelihood (OR = 13.9, SE = 1.15, $p < .01$) of completing their STEM degree than males who do not need math remediation (OR = .38, SE = .02, $p < .01$). The authors noted that these gender differences are more likely rooted in internalized factors based on environmental stereotypes and stressors, rather than objective observable factors. Due to the strong relationships demonstrated between demographic variables and mathematics, math ability should also be investigated further with regard to academic persistence and attrition in STEM majors.

Career Development and Intervention

Many career theories address career decision-making and career choice. The career theories that follow have been included in this review because of their relevance to variables pertinent to STEM retention. Research outcomes and implications for STEM programming will be discussed.

Theory of Circumscription, Compromise, and Self-Creation

Linda Gottfredson (1981) proposed a developmental theory that integrated the sociological and psychological approaches to career development. The aim of her Theory of Circumscription, Compromise, and Self-Creation was to explain emerging trends in occupational choice based on demographic factors, such as ethnicity/race, sex/gender, and social class. Within Gottfredson's (1981) framework, she defined circumscription as the process by which individuals eliminate occupations as possible careers based on interactions with society during their formative years. The process of circumscription occurs within four stages: (a) Orientation to size and power, (b) Orientation to sex roles, (c) Orientation to social valuation, and (d) Orientation to internal unique self. The second stage represents the primary time during which students' conceptualization of careers are influenced by societal gender norms and stereotypes; for example, children may come to believe that being a doctor is for boys and being a nurse is for girls. In the third stage, children begin to conceptualize how the dominant society assigns prestige and value to some occupations based on the type of work being done. Within these stages, children develop what Gottfredson labeled as *images of occupations*; these are the internalized stereotypes of occupations that individuals have related to whom they believe can work in an occupation and what kind of work they believe can be done by someone in that occupation.

As children develop, their self-concept is influenced by their appearance, gender, values, abilities, and personality, among other factors. They evaluate their images of occupations

against themselves and begin to eliminate career options from their future as early as four years old (Curry & Milsom, 2014). Over time, children can begin to adjust their preferred career options based on the external, or environmental, constraints that affect their beliefs about the attainability of a career (Zunker, 2016). This process is known as compromise (Gottfredson, 1981). Through her research, she found that individuals are more likely to compromise their area of career interest than their preferred level of prestige or sex type (i.e. careers they see as congruent with their internalized concept of gender roles) if there is a large discrepancy between what type of career they want to do and they type of career they perceive as possible (Zunker, 2016). If this same discrepancy between their preference and their perceived reality is moderate, they are more likely to compromise on sex type than prestige.

This process of circumscription and compromise is especially important with regard to STEM careers, as there are large disparities in STEM career attainment for women and people of color (NMSI, 2016; NSF, 2013; Palmer et al., 2011). Within the process of circumscription, children make judgments about the attainability of a career based on whether or not they see people like themselves in the career. If students from demographic groups who are underrepresented in STEM are not exposed to individuals representative of their population in STEM careers, these demographic patterns, according to Gottfredson's theory, may become cyclical (i.e. the cycle of underrepresentation will not break itself without an outside intervention propelling students from underrepresented groups into STEM fields). Mansfield et al. (2014) noted that these interventions are more appropriate at the K-12 level if differences are sought at the undergraduate level; however, they noted that such endeavors can be effective at the

undergraduate level. Such interventions should include exposing students to STEM faculty, graduate students, and industry professionals from underrepresented populations who can disrupt the images of occupations that students may have for STEM fields.

Theory of Vocational Choice

John Holland's (1973) theory seeks to connect individuals to a career that is congruent with their personalities, reflected by interests, skills, and values. His theory is one of the most widely used career theories in practice (Curry & Milsom, 2014). After studying the preferences and values of workers, Holland was able to create a system of classifying careers into personality types. The six primary personality types are Realistic (R), Investigative (I), Artistic (A), Social (S), Enterprising (E), and Conventional (C); these six personality types are presented as a hexagon, with each type representing a different zone of the hexagon (See Figure 1). Holland (1973) organized and categorized careers based on the top associated personality types for members of a particular career (e.g. the code for Astronomers is Investigative-Artistic-Realistic, or IAR). These groupings make it easier for individuals to explore similarities and differences between careers with similar codes.

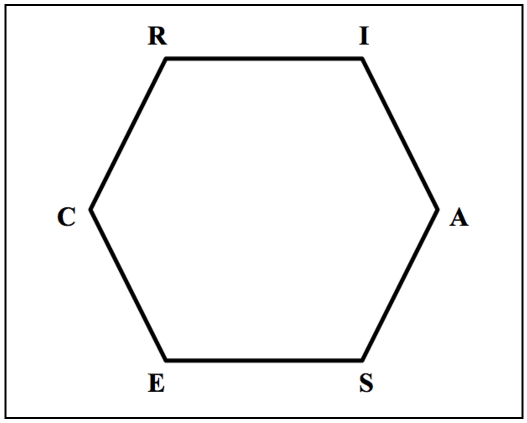

Figure 1. Holland's RIASEC Model

Through assessments based on Holland's theory, individuals can learn their top three personality types, represented by the three-letter code (e.g. Realistic-Conventional-Investigative, or RCI; Holland, Vierstien, Kuo, Karweit, & Blum, 1970). The primary personality type is listed first followed by the second and third highest type, which can help and individual better understand nuances or specific preferences within the primary type (i.e. an individual with a code of RCI will have somewhat different preferences than an individual with a code of ICR). If an individual's scores show that their top personality types are much higher than the remaining types, the individual's personality code is considered to be well differentiated (Curry & Milsom, 2014). An undifferentiated score indicates that the individual shows no discernable preferences toward a particular personality type, which could make narrowing career options more difficult for that person. Similarly, if an individual's top personality type preferences are adjacent to each other on the hexagon, his or her personality code is considered to be congruent (Holland, 1973).

Because careers were intended to be classified into congruent codes, an individual with an incongruent code may struggle to integrate all personality preferences into a particular career.

Researchers using Holland's model to make predictions about undergraduates in STEM have focused both on major selection and academic persistence (Le, Robbins, & Westrick, 2014; Porter & Umbach, 2006). Examining a sample of 1,665 undergraduate students, Porter and Umbach (2006) found that students with an investigative personality type were 17.4 percent less likely to choose an arts/humanities major over a science major, 9.3 percent less likely to choose an interdisciplinary major over a science major, and 14.2 percent less likely to choose a social sciences major over a science major ($p < .01$). In contrast, students with an artistic personality type were 25.4 percent more likely to choose an arts/humanities major over a science major, 7.6 percent more likely to choose an interdisciplinary major over a science major, and 10.0 percent more likely to choose a social science major over a STEM major. Whereas the authors noted that these findings could be supported by theory, they recognized several limitations of their study, including the relatively low reliability of their investigative personality scale ($a = .58$) and their use of a national data set with which they had no control of data collection procedures. Additionally, as these findings support questions related to Holland personality types and major selection, they do not address associations between personality types and persistence within a declared STEM major.

Le et al. (2014) examined both major selection and academic persistence for undergraduates in STEM based on Holland's model. The researchers used a longitudinal data

set from ACT of students (N = 207,093) at 51 four-year post-secondary institutions. First, the authors examined the likelihood of enrolling in a STEM major by calculating an Interest-fit coefficient (a Pearson's product-moment correlation between a student's interest profile score and an overall profile score for STEM fields, then converted to a Fisher's z). The researchers built this coefficient into the predictive model, with a higher Fisher's z score indicative of a better fit with the student's profile and the STEM profile (i.e. investigative and realistic). Students with a higher standardized interest fit coefficient were statistically significantly more likely to choose a STEM science (OR = 2.47, $p < .01$, Delta p [effect] = .06) or a STEM quantitative major (OR = 1.58, $p < .01$, Delta p [effect] = .05). Regarding persistence within STEM majors, students with a higher standardized interest fit coefficient were statistically significantly less likely to change to a non-STEM major (OR = .881, $p < .01$, Delta p [effect] = -.024. Despite small effect sizes, these results indicated that interest fit based on Holland's model is a stronger predictor of STEM major declaration than of persistence in STEM. One limitation of the study is that the authors only disaggregated STEM majors into two categories: STEM science and STEM quantitative.

Super's Life-Span Life-Space Theory

In contrast to Holland's career theory focusing on person-environment fit, Super's (1953, 1990) Life-Span Life-Space Theory explains career development as a process that evolves developmentally over time and within a variety of life roles (e.g. child, student, parent). Super also held that individuals are qualified for a variety of occupations based on their interests,

values, skills, personality traits, and self-concept (Niles & Harris-Bowlsbey, 2009). Career adaptability, or career maturity, refers to one's readiness to make career decisions, which can relate to career knowledge, career exploration activities, and the influence of one's environment (Niles & Harris-Bowlsbey, 2009; Savickas, 1997). Individuals become more ready to make career decisions as they progress through a series of ordered developmental tasks; stagnation with one task can lead to career indecision (Super, 1990).

The first stage in Super's model is Growth, which occurs during childhood; in this stage, children become attuned to the world-of-work through fantasy, play, and curiosity about careers (1990). Exploration, the second stage, occurs during adolescence and continues into early adulthood; learning about, trying out, and narrowing career options are crucial to this stage. Early to middle adulthood is the timeframe of the third stage, Establishment; in this stage, individuals become more committed to their career and take steps to advance and become stable within their field (Super, 1990). Maintenance and Disengagement are the final two stages; within these stages, individuals work to maintain their careers into late adulthood and begin to transition out of their careers, respectively. Whereas these stages can occur linearly for some individuals, others may cycle back through an earlier stage if that individual experiences a career or job shift.

The life space is also a very important aspect of Super's (1953, 1990) theory. He noted that as individuals develop, the salience of their roles within their environment will shift. For example, a child or adolescent might more readily identify with the role of child or student,

whereas an older adult might identify more with the role of citizen or pensioner (Niles & Harris-Bowlsbey, 2009). Super also noted that these roles are enacted within several key environments (e.g. the home, the school, the workplace, and the community (Super, 1953, 1990). The stages in the model are often visually represented in context to the life roles as a Life Career Rainbow, on which individuals can display the salience of a particular role at a particular stage (Super, 1990).

The Career Development Inventory (CDI; Glavin & Rehfuss, 2005; Super, Thompson, Jordan, Lindeman, & Myers, 1981) is a measure of career decidedness and career adaptability based on Super's theory. The CDI includes four subscales. Career Planning measures the extent to which an individual has engaged in career planning activities, whereas Career Exploration assesses one's awareness of resources and information pertaining to career decision making. The Decision Making subscale evaluates one's ability to make appropriate decisions with regard to careers, and the World-of Work subscale evaluates an individual's fund of knowledge regarding their career options. Higher scores on each subscale are indicative that an individual is more ready to make decisions about careers, whereas lower scores indicate that further knowledge or intervention is needed. With regard to STEM, no published studies were found that applied the CDI to a unique STEM population, particularly with regard to predicting academic persistence.

Social Cognitive Career Theory

A newer career development theory, Social Cognitive Career Theory (SCCT; Brown & Lent, 1996; Lent, 2005; Lent & Brown, 2002) frames the career development process, including self-efficacy, outcome expectations, interests, action, and performance. Due to the importance of self-efficacy to SCCT, the theorists pulled from Bandura's (1986) social cognitive theory, noting that self-efficacy is impacted by past performance on a task, vicarious learning, social persuasion, and physiological reactions. According to SCCT, these self-efficacy beliefs can impact outcome expectations, interests, goals, action initiation, and actual performance (Niles & Harris-Bowlsbey, 2009). Similarly, outcome expectations can impact interests, goals, and action initiation. For career development specifically, self-efficacy beliefs and beliefs about how one will perform in a career will impact whether a person chooses to go into a particular field, what steps are taken to be successful within that field, and task performance within that field. As with Gottfredson's theory, SCCT takes an individual's broader social context into account; however, SCCT uses a more cyclical model, rather than a linear model. This process cycles back and influences future self-efficacy and outcome beliefs, either for better or worse.

As discussed in prior sections, demographic factors, as well as one's perceived math ability, can impact self-efficacy and outcome beliefs for STEM fields. Based on Gottfredson's theory, individuals from underrepresented groups may have difficulty imagining themselves within some STEM fields; taking that sentiment further with SCCT, they may also not be able to see someone like them being *successful* in a STEM major (Niles & Harris-Bowlsbey, 2009).

Similarly, if one does not feel efficacious with mathematical ability, he or she may opt for a non-STEM major that requires fewer math classes.

Lent, Miller, Smith, Watford, Lim, and Hui (2016) tested the SCCT model with 908 engineering undergraduates across two universities. Using path analysis, the researchers concluded that intended persistence (i.e. wanting to finish) had the strongest direct relationship (path coefficient = .29) with actual academic persistence from the second year to the third year of college. The authors noted that several variables intervened between self-efficacy and actual academic persistence, including academic satisfaction and persistence intentions. Two limitations to this study include the fact that the researchers only examined engineering majors and that the study examined second and third-year students. Nevertheless, the study's results shed light on how self-efficacy and other factors related to career adaptability help predict retention in STEM.

In a similar study, Lee, Flores, Navarro, and Kangui-Munoz (2015) tested SCCT's academic persistence model with 350 White and Latino/a men and women. The results of the model established a statistically significant relationship between math/science ability (as measured by the ACT Math and Science tests) and students' first-year undergraduate grade point averages (path coefficient = .39, $p < .001$) and between math/science ability and engineering self-efficacy (path coefficient = .20, $p < .01$). The ACT alone had a small, albeit non-significant, relationship with actual persistence (path coefficient = -.02, $p > .05$), whereas college grade point average had a stronger relationship with actual persistence (path coefficient = .17, $p < .05$).

There were strong linear paths linking ability to self-efficacy to goals (path coefficient = .30, $p <$ .001) and goals to persistence (path coefficient = .36, $p < .001$). The overall model explained 17 percent ($R^2 = .17$) of the variance in persistence outcomes. Most notably, the model did not vary between White and Latino/a students [$\chi^2(7) = 10.38$, $p > .05$]. However, there were some differences by gender [$\chi^2(8) = 16.33$, $p < .05$]. The model explained 12 percent ($R^2 = .12$) of the variance in persistence outcomes for males and 35 percent of the variance in persistence outcomes for females ($R^2 = .35$), providing more support for the use of SCCT concepts with females in STEM. The authors did not include outcome expectations from the model, which limits the ability to test the effect of that variable.

In another study, Lent, Lopez, Lopez, and Sheu (2008) tested the Social Cognitive Career Theory model with students in computing disciplines and found that self-efficacy was a strong predictor of outcome expectations ($r = .71$, $p < .05$), interests ($r = .61$, $p < .05$), and major choice goals ($r = .30$, $p < .05$). Moreover, the model explained 44 percent ($R^2 = .44$) of the variance in self-efficacy, 50 percent ($R^2 = .50$) of the variance in outcome expectations, 40 percent of the variance in interests ($R^2 = .40$), and 33 percent of the variance in major choice goals ($R^2 = .33$). Lent et al.'s model fit well when the researchers separately added gender, ethnicity, education level, and university type (predominantly White institution or historically Black college/university) as grouping variables. This indicates that predictive models must take on a wide array of variables when predicting academic persistence in STEM. The researchers, however, only applied the model to one discipline within STEM with a population that was not representative of STEM overall.

The Cognitive Information Processing Approach

The Cognitive Information Processing (CIP) approach to career decision making focuses both on the content and the process of how individuals make decisions about their careers (Peterson, Sampson, & Reardon, 1991; Peterson, Sampson, Reardon, & Lenz, 1996; Sampson, Lenz, Reardon, & Peterson, 1999; Peterson, Sampson, Lenz, & Reardon, 2002). In essence, the goals of the CIP approach are to better understand a person's decision-making process and to help them make informed career decisions. Akin to Super's theory, CIP addresses career adaptability in practice and also examines how one's internal thoughts or processes impact career decision-making. As such, CIP helps individuals understand the nature of their career decision-making process and provides a framework that can be used to assist individuals in making career decisions (Peterson et al., 2002).

The content component of the career decision-making process incorporates knowledge of the individual, knowledge of the world of work, and knowledge of decision-making skills. CIP theorists graphically represented this content component of CIP with the Pyramid of Information Processing Domains (Peterson et al., 1991). The Knowledge Domain, or the base of the pyramid, includes self-knowledge and occupational knowledge; self-knowledge includes personal information (e.g. values, skills, interests) about an individual obtained through formal and informal career assessments, whereas occupational knowledge refers to knowledge about the world-of-work and about specific career fields. The Decision-Making Skills Domain, or the center of the pyramid, represents the process an individual uses to choose a career, major, or job that fits with his or her unique profile; within the context of CIP, this process is the CASVE

Cycle (Communication, Analysis, Synthesis, Valuing, Execution), which is the process component of CIP. The Executive Processing Domain, or the top of the pyramid, represents the metacognitions related to making career decisions; these metacognitions can include positive and negative self-talk and awareness of one's thoughts and feelings about career decision making.

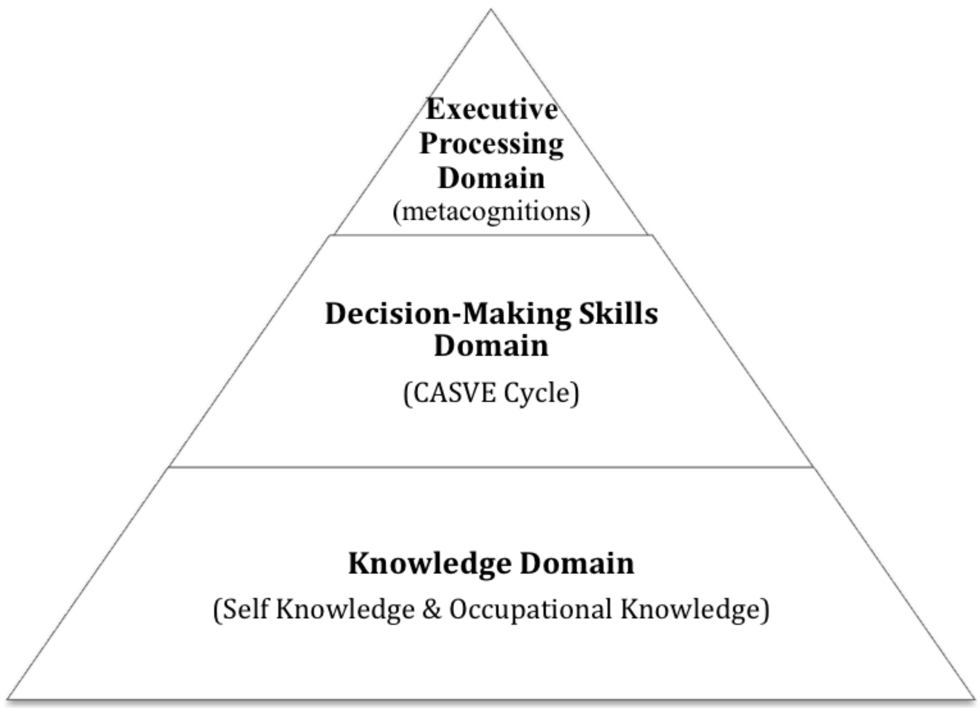

Figure 2. The Pyramid of Information Processing Domains of CIP

Making career decisions is one of the most important and powerful processes that shape the life of an individual (Hackett & Betz, 1995). Furthermore, career indecision, defined as the struggle with making decisions related to careers, is associated with reduced life satisfaction, lower career self efficacy, and heightened stress and anxiety (Jaensch, Hirschi, & Freund, 2015). Saunders, Peterson, Sampson, and Reardon (2000) found that depression and dysfunctional career thinking were significant predictors of career indecision. The authors further noted that

because dysfunctional career thinking contributes to problems with making career decisions, these negative career thoughts should be addressed prior to engaging in career exploration and planning.

The *Career Thoughts Inventory* is a measure of negative career thinking that provides a total score and three subscale scores: Decision Making Confusion, Commitment Anxiety, and External Conflict; the researchers derived these subscales from a series of principal component analyses with oblique rotation that identified a three factor structure. Higher scores on the CTI indicate more negative career thinking (Sampson, Peterson, Lenz, Reardon, & Saunders, 1996a). Using a generic sample of college students (*N* = 595), Sampson et al. (1996a) reported reliability coefficients for the CTI Total score (α = .96), the DMC subscale (α = .94), the CA subscale (α = .88), and the EC subscale (α = .77). Each of these coefficients falls within the acceptable to excellent ranges for internal consistency (DeVellis, 2012; Kline, 2000). They also reported 4-week test-retest correlations for the CTI Total score (r = .86), the DMC subscale (r = .82), the CA subscale (r = .79), and the EC subscale (r = .74) with the college student sample. The authors established convergent validity by correlating the CTI scales with the *My Vocational Situation* scale, the *Career Decision* Scale, the *Career Decision Profile,* and the *Revised NEO Personality Inventory*; with all three norming groups, the relationships between the CTI scales and the other instruments were in the direction expected based on theory, with the strongest correlations with the *Career Decision Scale*. The CTI has been studied with general populations, as well as with individuals with disabilities and incarcerated males (Dipeolu, Sniatecki, Storlie, & Hargrave, 2013; Meyer & Shippen, 2016; Sampson, Peterson, Lenz, & Saunders, 1996a). In

these studies, career development interventions reduced negative career thinking. However, these studies did not test it with an intervention or test it with particular career fields (e.g. STEM).

Prescod et al. (In press) examined differences in CTI scores with STEM interested and STEM declared undergraduates after their first semester of college; the study by Prescod et al. was a part of the same STEM program as the current dissertation. The STEM interested students (n = 99) took a STEM-focused career planning class to help them select a major, whereas the STEM declared students (n = 182) took a STEM seminar class designed for students majoring in STEM. Using a series of one-way ANOVAs, the researchers found statistically significant differences between the STEM interested and STEM declared students on the CTI Total [F (1,279) = 31.54, p = .000, eta^2 = .12] the CTI DMC subscale [F (1,279) = 32.68, p = .000, eta^2 = .11], the CTI CA subscale [F (1,279) = 18.86, p = .000, eta^2 = .07], and the CTI EC subscale [F (1,279) = 8.60, p = .000, eta^2 = .03]. The STEM decided group had lower CTI Total pretest scores (M = 31.64, SD = 20.55) and CTI Total posttest scores (M = 29.12, SD = 21.85) than the STEM interested group (Pretest: M = 50.52, SD = 19.41; Posttest: M = 36.07, SD = 21.94). Although the researchers did not report an F statistic for the differences within each group from pre to post, the mean scores demonstrated that the STEM interested group had a greater decrease in negative career thinking than the STEM declared group. These findings provided preliminary support for the STEM-focused Career Planning course as a means of helping students lower negative career thoughts; however, the lack of a true control group makes it difficult to reach a causal inference.

The researchers from the present dissertation and from the Prescod et al. (In press) study conducted a follow-up analysis, which has not yet been published at the time of this dissertation. In this analysis, the researchers tested the effect of an STEM-focused undergraduate Career Planning Course on students' negative career thoughts. Of the total sample, 214 undecided students participated in the Career Planning course; as a comparison group, 118 students who were recruited under the same criteria as the intervention group and who declared a major between the time of admittance to the program and the start of classes, took a STEM Seminar Course without a career development intervention focus (neither group was randomly assigned). As such, the Career Planning group began their first semester of college with higher CTI scores than the comparison group. After controlling for gender and between-group differences on the CTI and its subscales, an ANCOVA revealed that students who took the STEM-focused Career Planning course (*Madj* = 31.964, *SE* = 1.143) not only saw a larger reduction ($F_{1,325} = 7.274$, $p = .007$, $\eta^2 = .022$, $d = .309$) in their CTI Total scores but they also outgained the students who did not take the career planning class (*Madj* = 37.475, *SE* = 1.621). Despite the limitation of not having a true control group, the undecided students in the STEM-focused Career Planning course ended their first semester of college with lower adjusted CTI scores than the decided group. This pilot study provides support for the STEM-focused Career Planning course used within the present study.

In a second pilot analysis, the researchers included the CTI in a model predicting academic persistence in STEM from year one to year two (Belser, Prescod, Daire, Dagley, &

Young, 2017). For this analysis, 181 students were included in the career planning group, and 134 were included in the comparison group similar to the previous study. The results of the binary logistic regression indicated that students who took the career planning class were nearly three times (OR = 2.973) more likely to be retained in a STEM major from their first year to their second year. Moreover, changes in CTI Total scores showed a marginal ability to predict persistence in STEM majors from year one to year two (OR = .979). Although the change in negative career thinking was an inconclusive predictor of persistence in STEM majors, including the CTI Total score change variable did greatly improve the accuracy of the logistic regression model; however, the final model only predicted 43.3 percent of non-retained students correctly. The Hosmer and Lemeshow Goodness of Fit Test was approaching statistical significance (p = .07), which indicates that the final model was acceptable but did not have a good fit with the data set. The overall accuracy of the model would likely be improved by adding additional variables in the logistic regression to account for more variance. One limitation of this study is that it only included three independent variables, rather than applying a more comprehensive set of variables based on relevant literature. Additionally, the study only looked at the overall model accounting for the students who took the career planning class and those in the comparison group; if the study also examined these two groups individually using logistic regression, it is possible that the ability to predict retention in STEM would have been different for decided students than undecided students. Future research should consider this option to strengthen the findings of the study.

Other Career Planning Courses in Undergraduate Programming

Parks, Rich, and Getch (2012) noted that undergraduate students who participate in a career planning course are more likely to successfully matriculate through a major than students who do not participate in such coursework. Using a qualitative approach, the authors ascertained more detailed information about the undergraduates' experience in the program. The students indicated that participating helped build their self-esteem and helped them reinforce their career interests. They elaborated further noting that there was not a particular intervention that helped most; however, the overall process was helpful.

Folsom, Peterson, Reardon, and Mann (2004) studied the impact of a generic career planning course on academic performance and graduation. The authors used archival student data to evaluate a career planning course framed around Cognitive Information Processing (CIP). There were no significant differences between students who took the career planning class and those who did not take the career planning class with respect to months taken to graduate [$F(1,1083) = 1.095$, $p > .01$] and cumulative GPA [$F(1,1083) = 1.149$, $p > .01$]. There were, however, significant differences between students who took the career planning class and those who did not take the career planning class with respect to the number of credit hours taken to graduate [$F(1,1083) = 1418$, $p < .001$, $ES = .03$] and the number of course withdrawals [$F(1,1083) = 1.535$, $p < .001$, $ES = .08$]. These findings indicate that although not taking the career planning class did impact the students' ability to finish school or lower their GPA; however, but students did withdraw from more classes and take a larger courseload, likely to offset the dropped classes. When broken down by gender, females who took the career planning

class graduated in significantly less time than those who did not ($p < .01$; 50.1 vs. 60.8 months, adjusted). In contrast, males who took the career planning class did take longer to graduate (54.5 vs. 47.7 months, adjusted) but had fewer course withdrawals and higher GPAs. A limitation to the study is that the data used in the analysis came from students enrolled in one university from 1989 to 1993.

Reardon, Melvin, McClain, Peterson, and Bowman (2015) paired the participants from the Folsom et al. (2004) study with a comparison group of students from the same time period who did not take a career planning course; the comparison group had been matched through stratified random sampling. Although the groups had been matched based on specific criteria, a preliminary chi-square test indicated a significant difference in the graduation rates for the two groups ($\chi^2 = 15.47$, $df = 1$, $p < .001$), with 81.5 percent of the career planning group graduating within six years and 71.3 percent of the comparison group graduating within six years. Using binary logistic regression, the researchers found that participating in the career course, cumulative GPA, changes of major, and the number of course withdrawals were significant predictors of whether students would graduate within six years or drop out. The model accurately predicted approximately 95 percent of those who graduated but only about 58 percent of those who dropped out. The Nagelkerke R^2 was .560, indicating that the model explained about 56 percent of the variation in predicting whether students would drop out or graduate. It is notable that these results are similar to the findings of the first pilot study (Belser et al., In press). Although the groups were matched, the authors acknowledged excluding college seniors and

students who achieved less than a C+ in the course, which impacts the generalizability of the findings. The authors also encouraged future researchers to identify additional variables to include in predictive models. However, neither the Folsom et al. (2004) study nor the subsequent Reardon et al. (2015) study specifically focused on STEM students.

Much like the first pilot study for this dissertation, Osborn, Howard, and Leierer (2007) studied the effect of a six-week career development course on negative career thoughts of racially and ethnically diverse college freshmen. With a sample of 158 students, the authors examined CTI scores as pre and post-tests. There were no significant differences in pre-test CTI scores based on gender or ethnicity [F (1, 150) = 2.71, p > .05]. When looking at the effect for the course, the authors found a significant multivariate effect on students' CTI Total scores [Wilks' lambda = .79, F(1,157) = 40.94, p < .001, η^2 = .21], with the post-test being significantly lower than the pre-test. This study helps establish a link between career development coursework and reductions in negative career thinking. The participants in the study were part of a targeted first-year experience program not specific to any particular major, which indicates that one should take caution in generalizing to the overall population of college freshmen. One noteworthy distinction of this study is that it indicated that similar results could be achieved in a 6-week course that had previously been seen in a 14-15 week course. The authors recommended examining longitudinal data to follow up with participants to identify the more long-term effects of the course (Osborn et al., 2007).

Similar to other aspects of STEM programming, career related coursework has more commonly focused on students with declared STEM majors, rather than undeclared students. In one such class for biology majors, the primary focus was on orienting students to the field of biology and to the biology program at that particular university (Freeman, 2012). Students were tasked with identifying a career path by taking the *Strong Interest Inventory*, meeting with a staff member from the university's Career Center, completing a side-by-side analysis of six possible careers, and other in-class activities. Once students identified their intended path, they created a detailed career plan. Students revealed through end-of-course surveys that they better understood the field of biology and their major program after taking the course. One noteworthy item from the survey was that after completing the course, students' self-reported ability to articulate their career plan and its appropriateness significantly increased for the first year (t = 10.565, df =42, $p < .05$) and second year (t = 3.914, df =39, $p < .05$) the course was offered (Freeman, 2012). Although this course was among the few that address career exploration within STEM, it was not targeted at undecided students; moreover, it was dependent on self-report data for outcome evaluation and did not track students beyond the end of the course.

In another STEM-focused project, Gentile et al. (2012) described an integrated science course for first semester STEM majors taught by an interdisciplinary team of ten STEM faculty members that focused on key concepts of each major field, as well as interdisciplinary research collaborations. After completing the course, students were more likely to participate in undergraduate research experiences in a subsequent summer. For the first year the course was

offered, all 20 (100 percent) of the students engaged in undergraduate research the first summer after the course, and 12 students (61 percent) engaged in a second summer of research; in the comparison group, only 9 percent engaged in research in their first summer and only 22 percent engaged in research their second summer. Students involved in the course were more likely to take additional coursework in multiple STEM disciplines; approximately 94 percent of students who took the integrative science course enrolled in multiple subsequent STEM courses, as opposed to 73 percent of students in the comparison group. Students who took the integrated science course (94 percent) were also more likely to maintain or declare a major in a STEM discipline by the end of their second year than students at the university who did not take the course (60 percent). The instructors acknowledged that their data was preliminary and did not represent the most effective way of evaluating the impact of the course; however, they recognized that this type of activity did have positive effects. In addition, although the course helped students become more acquainted with major fields, it did not have a career development focus to match students with a field that fits their individual profile, and it only tracked students through their second year.

Implications

Low rates of academic persistence, or retention, in STEM indicate a clear problem based on the prevalence of students beginning a STEM major and not completing that major. Previous studies examined demographic variables as they relate to STEM major declaration and academic persistence in STEM majors (Beasley & Fischer, 2012; Foltz et al., 2014; Gayles & Ampaw,

2014; Litzler et al., 2014; Riegle-Crumb & King, 2010). Many of these studies, though, focused primarily on students who were already preparing to declare a STEM major, rather than undecided STEM-interested students. Similarly, with mathematics, studies revealed that math ability (measured by the SAT), efficacy beliefs about math, and math stereotype threat can affect one's decision to choose a STEM major and be successful in that STEM major (Carnevale et al., 2011; Chen, 2013; CollegeBoard, 2012; Cundiff et al., 2013; Nosek & Smyth, 2011).

Researchers have not studied STEM career development and career development interventions to the degree that they examined other constructs, such as demographics and math ability. The existing studies primarily focused on career interest as a predictor for STEM declaration and persistence (Le et al., 2014; Porter & Umbach, 2006). Career-related studies addressed discipline-specific self-efficacy combined with math aptitude to predict academic persistence (Lee et al., 2015; Lent at al., 2016; Lent et al., 2008); these studies however examined students with declared STEM majors or who were preparing to declare a STEM major. Similarly, researchers and instructors of STEM-focused career planning classes noted that these courses catered to students who were already STEM decided (Freeman, 2012; Gentile et al., 2012). After exhaustive literature searches using multiple academic databases, the researcher found only one study (Belser et al., 2017) that incorporated a career planning intervention and measures of career readiness into predictive models of STEM retention. As the analysis in that study yielded significant results related to the career planning course utilized in the present study and academic persistence of its participants, these variables warrant further research.

To date, no published studies have integrated demographic variables (gender and ethnicity), math ability (SAT math scores and math placement scores), and measures of career readiness (CTI) into one predictive model for academic persistence in STEM. Additionally, investigating these constructs with both undeclared STEM-interested and STEM-declared students can further the literature on the extent to which these variables can predict academic persistence in STEM. Moreover, discerning the ability of these variables to predict which students are at risk for dropping out of STEM majors can help drive STEM initiatives targeting recruitment and retention.

CHAPTER III: METHODOLOGY

Introduction

Current undergraduate retention rates for science, technology, engineering, and mathematics (STEM) disciplines contribute to a national STEM Crisis (Chen, 2013; NSF, 2013; NAS, 2011). Chen (2013) reported that the declaration rate for undergraduate STEM majors is less than 30 percent and that nearly half of these students leave their STEM major prior to graduation. Universities and colleges around the country developed programs on their campuses targeting STEM recruitment and retention, with particular focus on increasing engagement with underrepresented populations (Bouwma-Gearhart, Perry, & Presley, 2014; Defraine, Williams, & Ceci, 2014; Palmer, Maramba, & Dancy, 2011; Schneider, Bickel, & Morrison-Shetlar, 2015). In prior studies related to STEM engagement and retention, researchers investigated the influence of demographics and math ability; however, they overlooked career development factors related to STEM retention (Cundiff, Vescio, Loken, & Lo, 2013; Gayles & Ampaw, 2014; Riegle-Crumb, Grodsky, and Muller, 2012).

In the present study, the researcher sought to provide a preliminary investigation into whether demographic factors, math ability, and career development factors could predict undergraduate retention in STEM majors. At present, researchers have not employed these three constructs together in studies examining undergraduate STEM retention outcomes. The outcomes of this quantitative study may provide valuable information for STEM engagement

researchers, higher education professionals, post-secondary career development professionals, and counselor educators.

Research Design

The current study was part of the UCF COMPASS Program, a larger federally funded research collaborative between multiple senior colleges at the University of Central Florida. The larger project recruited undecided admits to the University with high math potential (i.e., SAT Math scores at or above 550) and a potential interest in STEM to be a part of a STEM recruitment and retention program. The program offered the STEM-focused Career Planning course discussed within this dissertation, as well as math and science tutoring, peer mentorship, and an undergraduate research experience. All students admitted to the COMPASS Program were undecided at the time of admission, but some students selected a STEM major between admittance and the first day of classes. The undecided students enrolled in the STEM-focused Career Planning course, and the students who selected a STEM major instead took a STEM Seminar course that focused on engaging students with their majors rather than career planning. The primary initiatives of the COMPASS program (e.g., the two courses, the peer mentors) operate in students' first year at the University. However, students have access to math and science tutoring throughout their college years and can take part in an undergraduate research experience in their second year of college.

For this dissertation, the researcher used data from the COMPASS Program and employed a quasi-experimental, quantitative design using non-equivalent comparison groups (Campbell & Stanley, 1963; Gall, Gall, & Borg, 2007). The researcher obtained the sample of

undergraduate students through purposive criterion sampling with non-random assignment, necessitating the use of a quasi-experimental design (Gall et al., 2007). Moreover, the primary grouping variable related to the participants' membership in one of the two tracks of the COMPASS Program. One track takes a STEM-focused Career Planning course in their first year, and the other track takes a STEM Seminar course without a career development focus. The researcher further defines these two tracks in a later section.

The study aimed to determine which variables are related to first and second year retention in undergraduate STEM majors. The researcher chose to analyze the contributions of the independent variables using binary logistic regression due to the binary nature of the outcome variables, which the researcher coded as retained or non-retained (Agresti, 2013; Hosmer, Lemeshow, & Sturdivant, 2013; Tabachnick & Fidell, 2013). Whereas, discriminant analysis and logistic regression both operate to predict outcomes based on a dichotomous categorical variable, logistic regression offers more flexibility to non-normally distributed independent variables (Hosmer et al., 2013). The data set for this study contained continuous variables derived from career assessment results that are non-normally distributed based on the population. Therefore, the researcher determined logistic regression to be a more appropriate analysis for the proposed dependent variables. Additionally, the proposed model for this study includes both categorical and continuous predictors.

Whereas structural equation modeling (SEM) provides a more robust procedure for making predictions and understanding the interrelatedness of predictor variables, Tabachnick and Fidell (2013) noted that "SEM assumes that measured variables are continuous and measured on

an interval scale" (p. 734) and that nominal variables can be included as independent variables through the use of dummy coding. Hair, Hult, Ringle, and Sarstedt (2014) reiterated that researchers commonly use nominal (i.e. categorical) variables in SEM studies as categorical control variables or moderating variables. Hair, Sarstedt, Pieper, and Ringle (2012a) further posited that when researchers use a binary single item (e.g. retained/not retained) to measure an endogenous latent variable, "a basic premise of the ordinary least squares regression is violated (p. 326). Hair, Sarstedt, Ringle, and Mena (2012b) more explicitly warned researchers not to use categorical variables as endogenous constructs and noted that using categorical variables to split the dataset in multigroup comparisons is a more appropriate function. Kupek (2006) proposed a strategy for using Yule's transformation to convert results from a logistic regression to a continuous correlation coefficient that can then be used in an SEM analysis; however, the author noted that this approach would require a logistic regression model with good model fit in order to take this next step. Because of the recommendations against using SEM with categorical outcome variables (Hair et al., 2014; Hair et al., 2012a; Hair et al., 2012b; Tabachnick & Fidell, 2013), the researcher opted to use logistic regression to analyze the categorical dependent variables (Hosmer et al., 2013).

Rather than identifying a linear regression equation, as with a traditional linear regression, logistic regression functions to determine the natural ($\log_e$) of the probability that a case will be "in one group divided by the probability of being in another group" (Tabachnick & Fidell, 2013, p. 440). Logistic regression achieves this goal by making comparisons between the observed outcome values and the predicted outcome values from the proposed model both with and without the independent variables (Hosmer et al., 2013). The statistical model yields

coefficients for a regression equation and odds ratios, which serve as a measure of effect size (Tabachnick & Fidell, 2013). Multiple options exist for researchers to enter predictors into a logistic regression model, including entering them all at once, entering them purposefully (i.e. selecting predictors based on theory and prior research with less regard for the predictor's observed statistical significance), or entering them using a stepwise approach (i.e. predictors are added or removed from the model based on statistical significance to achieve the most parsimonious model; Hosmer et al., 2013). Although the researcher selected predictor variables based on theory and prior literature, this study employed a backward stepwise approach, in which SPSS removed non-significant predictors in order to achieve the most parsimonious model. The researcher opted for this approach to determine if removing the least significant variables would improve the models' ability to predict retention outcomes. Tabachnick and Fidell (2013) cautioned that a stepwise approach can lead to underfitting the model (i.e., leaving out predictors that are important based on theory), but this approach can have value in exploratory model building when a theoretical model is not structured enough to enter variables hierarchically (Field, 2009). To mitigate the possibility of underfitting, the researcher used a more liberal cutoff point ($p \leq .20$) for the inclusion of predictors in the model.

Population and Sample

The population for the current study was undergraduate students from the University of Central Florida (UCF) participating in UCF COMPASS (Convincing Outstanding-Math-Potential Admits to Succeed in STEM), a grant-funded research project focused on recruiting and retaining students in STEM majors (National Science Foundation STEP 1B: No. 1161228).

All participants in the study entered the COMPASS program and the university as first-year students between Fall 2012 and Fall 2015. Some COMPASS participants had earned enough college credits through high school programming, such as Advanced Placement coursework and Dual Enrollment, to be designated as sophomores or juniors; therefore, the term *first-year students* will be used in place of *freshmen* throughout this dissertation to refer to undergraduate students who are in their first year at UCF. The COMPASS program used purposive criterion sampling for selection into the program and the researcher ultimately used the same approach in obtaining the sample for this study (Gall et al., 2007). To be admitted into the UCF COMPASS program, applicants needed to (a) be first-year students at UCF, (b) have a SAT Math score of 550 to 800, (c) have an undeclared major status, and (d) have a potential interest in pursuing a STEM major. Additionally, to be eligible for this particular study within the overall COMPASS research endeavors, participants needed to have joined the COMPASS program by the Fall 2015 semester in order for them to complete at least one year of college by the beginning of the data analysis. Recruitment for the COMPASS Program included mail-outs to undecided UCF applicants and admits, presentations by COMPASS staff at orientation events, distribution of information about the program to area high schools, and a COMPASS program website.

To determine if the sample size of participants would yield adequate statistical power for the analyses, the researcher conducted an *a priori* power analysis for the hypotheses using G*Power 3 (Cohen, 1992; Faul, Erdfelder, Lang, & Buchner, 2007). For the power analysis for binary logistic regression, the researcher utilized an alpha level of .05, a recommended power of .80 (Cohen, 1992; Tabachnick & Fidell, 2013), and a corresponding odds ratio of 3.0. Results

from the power analysis indicated that a sample of 97 participants was necessary to ensure adequate power. As the sample for hypotheses one through three was 429 and the anticipate sample for hypotheses four through six was 271, the researcher expected the sample size to be sufficient for the study.

With logistic regression, statistical theorists also recommend comparing the ratio of cases in each outcome of the dependent variable to the number of independent variables used as predictors (Agresti, 2013; Hosmer et al., 2013; Tabachnick & Fidell, 2013). As a rule of thumb, Peduzzi, Concato, Kemper, Holford, and Feinstein (1996) recommended that there be at least 10 cases per outcome for each predictor included in the model, particularly with categorical predictors. However, Field (2009) and Vittinghof and McCulloch (2006) recommended a minimum of 5 cases per outcome for each predictor. The model proposed in the current study included ten independent variables as potential predictors. For hypotheses one through three, all independent variables met this rule of thumb sufficiently except Ethnicity because multiple subcategories (Asian/Pacific Islander and Other) within this variable had fewer than 10 cases in each outcome. Similarly, for hypotheses four through six, all independent variables met this rule of thumb except Ethnicity, with three of the five subcategories (African American/Black, Asian/Pacific Islander, and Other) having fewer than 10 cases in each outcome. Hosmer et al. (2013) noted that having an insufficient number of cases could lead to overfitting or underfitting the model, but also clarified that these are recommended guidelines, rather than strict rules. Collapsing the Ethnicity variable into smaller categories (e.g. Minority / Non-Minority) would resolve the violation of these recommendations but would detract from the researcher’s ability to

investigate each Ethnicity group individually, as recommended by prior literature on STEM retention. As such, the researcher opted to keep the Ethnicity variable coded as is instead of collapsing categories further, accepting a potential limitation to the study.

Data Gathering/Collection Procedures

This study is part of a larger ongoing grant-funded research project previously approved by the University's Institutional Review Board. Undergraduate participants in the study signed an informed consent document during their university orientation meeting. This informed consent document described the nature of the research being conducted, announced the types of data/assessments that will be collected and used, and explained that participation in the study is voluntary. Data collection for this project began in Fall 2012.

As stated, the UCF COMPASS program targets recruitment and retention in STEM majors for undergraduate students. As members of the program, students take their math courses with other students in the program and have access to math tutoring in a center designated solely for members of the program. As intended by the program's initial design, undecided and undeclared students take a STEM-focused career planning course in their first year to help them solidify their major choice. Some participants are officially coded as "undeclared" (i.e. they have not formally selected a major with the university), whereas others have listed a possible major based on a preliminary unconfirmed interest (e.g. Undecided Engineering, Undecided Science) or have listed a "dummy" major to which they have not committed (e.g. Biology, Psychology). Some participants formally commit and declare a STEM major between the time of admission to the program and the first day of class, and these students instead take a STEM

Seminar class in their first year focused on available opportunities within their STEM majors. Whereas the seminar class does provide opportunities for participants to learn more about their majors, it does not have a career development focus as with the career planning course. The program requires students in both tracks to participate in weekly study hours at a designated center. COMPASS students have a peer mentor in their first year of college, and female students have another opportunity to participate in additional programming that connects them to female peer mentors, female STEM faculty, and female STEM industry professionals. Similarly, to address issues of demographic representation in STEM found in the literature, the COMPASS Program intentionally includes females and ethnic minorities, as well as an intersection of the two, as guest speakers and peer mentors. Moreover, both the Principal Investigator and Project Director for the program are female administrators.

The Career Planning course is a modified version of the University's general career planning course. To meet the needs of STEM-interested students, the course focuses primarily on exploring STEM careers in a three-phase process. In the first phase, students take a battery of career assessments, which are used to help them understand their readiness to make decisions about careers, as well as their interests, values, skills, and personality. During the second phase, students learn more about their options within STEM by hearing from a variety of STEM faculty, researchers, and industry professionals; students also have an opportunity to visit the research labs of the STEM faculty. In the final phase, students use what they have learned over the semester to develop a career action plan and to research in depth the majors they are now

considering. Also in the course, students gain practice with developing a resume and cover letter, with interviewing for jobs, and with delivering a structured presentation about themselves.

The STEM Seminar course is designed for students who have declared a STEM major and provides supports for their success in that major. The course explores practical information topics, such as learning styles and strategies, time management and study skills, professional opportunities for STEM majors, undergraduate research for STEM majors, and engagement with the learning community. A variety of guest speakers from STEM industry fields and campus resource offices present students with information on how to maximize their success as a STEM student. Additionally, in lieu of lectures and guest presentations, certain class meetings operate as study and review sessions for math courses with tutors available.

The University's Institutional Knowledge Management (IKM) Office provided much of the data used in this study to the Project Director for UCF COMPASS. These data included demographic variables (gender and ethnicity), academic data (SAT Math scores and Math Placement Test scores), major related variables, and enrollment verification used to determine major retention and attrition. Receiving this data from the IKM Office eliminated the need for participants to complete a demographic questionnaire. The IKM Office provided the data in a series of comma separated values (CSV) files. The researcher transferred the data points of interest to a Statistical Package for Social Sciences (SPSS, Version 24) file and replaced student names with a unique COMPASS ID number.

Students completed the Career Thoughts Inventory (CTI) in either the Career Planning class or the STEM Seminar class. Students took the CTI at the beginning and end of the respective program course in which they were enrolled. For the Career Planning class, the CTI was a graded assignment that became a focal point of many in-class discussions pertaining to individual career development. For the STEM Seminar class, students received participation points for completing the CTI; whereas the CTI was not a primary topic of class discussion, students did receive an in-class explanation of their results. Because the CTI was used as an in-class assignment with both groups, the researcher did not provide additional incentives for participants beyond an assignment grade or participation points. The researcher and a team of trained research assistants added scores to the SPSS file.

Instruments and Scale Variables

The COMPASS program utilizes scores from a variety of assessments; however, the researcher only used three of these assessments within this study. The Career Thoughts Inventory (CTI) was the only of these assessments that was directly administered and scored within course components of the program. The SAT Math subtest and the Math Placement Test were administered outside of the COMPASS program and were used by the university for admissions, advising, and scheduling purposes.

Career Thoughts Inventory

The Career Thoughts Inventory (CTI) is a 48-question assessment that measures negative career thinking (Sampson, Peterson, Lenz, & Saunders, 1996a; Sampson Peterson, Lenz, & Saunders, 1996b). Respondents are asked to read statements about careers and indicate their level of agreement with the statement based on a four-point Likert-type scale ranging from Strongly Disagree to Strongly Agree (represented numerically on a scale of 0 to 3, respectively). The CTI contains three subscales: (a) Decision Making Confusion (DMC), (b) Commitment Anxiety (CA), and (c) External Conflict. The DMC subscale measures the degree to which one is experiencing confusion or distress about making career-related decisions or narrowing their career options. The CA subscale measures the degree to which one is experiencing anxiety about committing to a specific career option. The final subscale, EC, measures the degree to which the thoughts and opinions of others hinder the career decision-making process.

The CTI provides a raw score and a *T* score for the CTI Total and for each of the subscales. The CTI Total raw score is the sum of all of the numerical item responses (i.e. the 0 to 3 score associated with the Likert-type labels); this score can range from 0 to 144. Each of the subscale raw scores is the sum of the items associated with the particular subscale. DMC scores range from 0 to 42, CA scores range from 0 to 30, and EC scores range from 0 to 15; the variability in these scales is due to some scales having more associated items. Raw scores can be converted to *T* scores using a graph on the back of the test booklet and compared to one of the norm groups (high school student, college student, or adult). Higher raw scores and *T* scores

indicate more negative career thinking. The mean *T* score (50) is the decided cut score with standard deviations of 10; scores above the mean are indicative of problematic negative career thinking. *T* scores between 51 and 60 are considered to represent a mild problem with negative career thinking, *T* scores between 61 and 70 are considered to represent a moderate problem with negative career thinking, and *T* scores at or above 71 are considered to represent a more severe problem with negative career thinking. This study will utilize a change score calculated by subtracting the pre-test score from the post-test for the CTI Total score and the three subscales.

Sampson et al. (1996a) provided psychometric information on the CTI's reliability and validity. Regarding internal consistency, alpha coefficients ranged from .93 to .97 for the CTI Total score, ranged from .90 to .94 for the Decision Making Confusion subscale, ranged from ranged from .79 to .91 for the Commitment Anxiety subscale, and ranged from .74 to .81 for the External Conflict subscale. Each of these coefficients falls within the acceptable to excellent range for internal consistency (DeVellis, 2012; Kline, 2000). Test-retest reliability coefficients were reported based on a 4-week interval; coefficients ranged from .69 to .86 for the CTI Total score, from .70 to .79 for the Decision Making Confusion subscale, and from .52 to .74 for the External Conflict subscale. Using the Reliability Analysis procedure in SPSS, the researcher found alpha coefficients for the CTI pretest of .95 for the CTI Total score, .87 for the DMC subscale, .88 for the CA subscale, and .71 for the EC subscale; similarly, the researcher found alpha coefficients for the CTI posttest of .96 for the CTI Total, .92 for the DMC subscale, .89 for the CA subscale, and .83 for the EC subscale. These measures of internal consistency were

within the same ranges as the coefficients of Sampson et al. (1996a), with the exception of the EC subscale that was .03 lower than the norm group but still within the acceptable range (DeVellis, 2012; Kline, 2000).

The test developers established content validity through the CTI's conceptual basis on Cognitive Information Processing (CIP) Theory and the CASVE Cycle of CIP (Reardon, Lenz, Sampson & Peterson, 2011; Reardon & Minor, 1975; Sampson et al., 1989). The CTI Total score, the Decision Making Confusion subscale score, and the Commitment Anxiety subscale score showed strong correlations with all eight content dimensions of CIP Theory; the External Conflict subscale score showed a mixture of moderate and strong correlations with all eight content dimensions of CIP Theory. Construct validity was established through a series of principal component analyses that resulted in three identifiable factors, which became the three subscales; these factors were replicated in subsequent studies and across the norm groups. The authors reported that criterion-related validity was established through multivariate analysis of variance, which revealed that the CTI could discern between individuals seeking career services and those not seeking career services. The test creators established convergent validity by comparing the CTI to the *My Vocational Situation* assessment, the *Career Decision Scale*, the *Career Decision Profile*, and the *NEO Personality Inventory-Revised*; for all three norming groups, the relationships between the CTI scales and the other instruments were in the direction expected based on theory, with the strongest correlations with the *Career Decision Scale*.

SAT Math

The SAT is a college admissions test commonly used by universities and colleges around the United States (CollegeBoard, 2016). High school students often take it during their junior and senior years. The SAT includes four subtests: (a) Essay, (b) Critical Reading, (c) Writing, and (d) Mathematics. The overall score ranges from 600 to 2400, whereas the scores on the three non-essay subtests ranges from 200 to 800 (CollegeBoard, 2016). Although Ewing, Huff, Andrews, & King (2005) reported psychometric properties for the entire instrument, the researcher only presented the properties for the SAT Math subtest, as only this subtest was utilized in this study. Participants for this study took the SAT prior to being admitted to the University and the COMPASS Program. Thus, the researcher treated these as existing data.

The SAT Math subtest includes 54 questions/tasks related to math fluency, conceptual understanding, and applications. Students have 70 minutes to complete them (CollegeBoard, 2016). Ewing et al. (2005) tested the validity of the SAT using a sample of 485 high school juniors; the sample was fairly representative with regard to gender and ethnicity. The authors reported an internal consistency coefficient of .92, with coefficients ranging from .68 to .81 for the four measured skill areas. They found an alternative-form reliability coefficient of .91 for math, with coefficients ranging from .71 to .78 for the four measured skill areas. The researcher could not analyze psychometric properties of the SAT Math subtest with this dataset as the IKM Office only provided composite scores, rather than individual items for each participants.

It must be noted that numerous research studies over several decades have highlighted potential test bias with the SAT based on race, indicating that lower mean family income and

decreased access to SAT preparation courses contributed to Black students scoring lower on the SAT than their White counterparts (Dixon-Román, Everson, & McArdle, 2013; Lawlor, Richman, & Richman, 1997; Temp, 1971; Toldson & McGee, 2014). Consequently, CollegeBoard revised the SAT in 2016 to address these concerns (after the completion of data collection for this study), and many universities have changed admissions and decision-making polices regarding the use of college entrance exams (CollegeBoard, 2017; Toldson & McGee, 2014). Despite these potential limitations, the SAT remains one of the most commonly used college entrance exams and has been used in numerous research studies, to which these results can be compared (CollegeBoard, 2017).

UCF Math Placement Test -- Algebra

The UCF Math Placement Test (MPT) is a university-made test that measures competence in three subtest areas: (a) algebra, (b) trigonometry, and (c) pre-calculus (UCF, 2016). This web-based test is administered to all first-time undergraduate student admits to determine which math course is the most appropriate starting point. When data collection began, all students were not required to take the MPT, but due to a policy change, all first-time undergraduate admits were required to take it; as a result, some students who joined the COMPASS Program during the early stage of data collection did not have an MPT score.

For this study, the researcher only utilized scores from the Algebra subtest as it is the only subtest that all students must complete when taking the MPT. Students only take the consecutive subtests if their scores on the Algebra subtest are above a particular threshold. Individuals are allowed 1 hour and 45 minutes to complete the 25 questions on the algebra sub-

test. If students complete the algebra subtest with 70 percent accuracy, they are given an opportunity to take the trigonometry and pre-calculus sub-tests. Each of these two sub-tests contains 15 questions, and students are given a maximum of 1 hour and 15 minutes to complete each section. The maximum score for the algebra sub-test is 500, and the maximum score for each of the trigonometry and pre-calculus sub-tests is 510. Psychometric properties for the Math Placement Test were not available. As with the SAT Math test, students take the Math Placement--Algebra test prior to the first day of classes to determine placement into math courses; thus, the researcher treated this variable as existing data. The researcher could not analyze psychometric properties of the UCF Math Placement--Algebra test with this dataset as the IKM Office only provided composite scores, rather than individual items for each participants.

Research Hypotheses

The aim of this study was to investigate the degree to which retention in STEM majors can be predicted by demographic variables, math ability, and career development factors. More specifically, this study aimed to explore ten variables within these categories in the context of first year to second year retention and first year to third year retention. Because of the inherent differences between the Career Planning group and STEM Seminar group (i.e., undecided vs. decided, respectively), the researcher also chose to examine the influence of the independent variables on each of these groups separately. As such, the researcher tested the following hypotheses using quantitative research methods:

Null Hypothesis 1: First-year to second-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, STEM Course Participation (Career Planning vs. STEM Seminar), and CTI change scores.

Null Hypothesis 2: First-year to second-year undergraduate retention in STEM majors for students participating in a STEM-focused Career Planning Course cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 3: First-year to second-year undergraduate retention in STEM majors for students participating in a STEM Seminar Course (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 4: First-year to third-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, STEM Course Participation (Career Planning vs. STEM Seminar), and CTI change scores.

Null Hypothesis 5: First-year to third-year undergraduate retention in STEM majors for students participating in a STEM-focused Career Planning Course cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 6: First-year to third-year undergraduate retention in STEM majors for students participating in a STEM Seminar Course (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Independent Variables

The study included ten independent variables as predictors for the logistic regression models. Each variable is discussed below:

Gender

The University's Institutional Knowledge Management Office provided participants' gender classification. This binary variable was coded as Male = 1, Female = 0. The University's reporting system used a binary classification for gender, rather than providing an Other option or specific options for students identifying outside of a traditional binary gender identity.

Ethnicity

The University's Institutional Knowledge Management Office provided participants' ethnicity classification. This variable was coded into five categories determined by the University's reporting system: (a) White = 1, (b) African American/Black = 2, (c) Hispanic/Latino = 3, (d) Asian/Pacific Islander = 4, and (e) Other = 5.

Initial Major

Initial major represents the major that participants listed on their application to the University prior to admission, which the Institutional Knowledge Management Office provided. This variable was coded as (a) Undeclared = 1, (b) Declared STEM = 2, and (c) Declared non-STEM = 3.

STEM Course Participation

This variable indicated whether participants were enrolled in the STEM-focused Career Planning class or the STEM Seminar class during their first year at UCF. The variable is coded as STEM Career Planning = 1, STEM Seminar = 0.

Career Thoughts Inventory (CTI) Total Change Score

The CTI Total score is a continuous variable. These data are collected at the beginning and end of participants' first semester with the COMPASS Program in one of the program's respective courses. To account for the changes in negative career thinking after participating in

either the Career Planning class or the STEM Seminar, the researcher computed change scores for the CTI Total by subtracting the pretest from the posttest.

Career Thoughts Inventory (CTI) Decision Making Confusion Change Score

The CTI Decision Making Confusion (DMC) subscale score is a continuous variable. These data are collected at the beginning and end of participants' first semester with the COMPASS Program in one of the program's respective courses. To account for the changes in negative career thinking after participating in either the Career Planning class or the STEM Seminar, the researcher computed change scores for the CTI DMC subscale by subtracting the pretest from the posttest.

Career Thoughts Inventory (CTI) Commitment Anxiety Change Score

The CTI Commitment Anxiety (CA) subscale score is a continuous variable. These data are collected at the beginning and end of participants' first semester with the COMPASS Program in one of the program's respective courses. To account for the changes in negative career thinking after participating in either the Career Planning class or the STEM Seminar, the researcher computed change scores for the CTI CA subscale by subtracting the pretest from the posttest.

Career Thoughts Inventory (CTI) External Conflict Change Score

The CTI External Conflict (EC) subscale score is a continuous variable. These data are collected at the beginning and end of participants' first semester with the COMPASS Program in

one of the program’s respective courses. To account for the changes in negative career thinking after participating in either the Career Planning class or the STEM Seminar, the researcher computed change scores for the CTI EC subscale by subtracting the pretest from the posttest.

Math Placement--Algebra Subtest Scores

The University’s Institutional Knowledge Management Office and the Math Department provided participants’ Math Placement Test scores, including scores for the Algebra subtest. Programmatically, University advisors and COMPASS Program staff use these scores to make decisions about advising and scheduling of students’ math courses. For this study, the researcher only used the Algebra subtest scores and entered them as continuous scores.

SAT Math Scores

The University’s Institutional Knowledge Management Office provided participants’ SAT Math scores. The university used these scores for purposes of admission to the university; additionally, students admitted to the COMPASS Program must have a minimum SAT Math score of 550. For this study, the researcher entered them as continuous scores.

Dependent Variables

In this study, the researcher analyzed two binary dependent variables. The first was Year Two STEM retention, which represented whether students were retained in a STEM major from their first year to their second year; the researcher used this variable with Hypotheses one

through three. The second dependent variable was Year Three STEM retention, which represented whether students were retained in a STEM major from their first year to their third year; the researcher used this variable with Hypotheses four through six. Both variables are binary and are coded as 1 = Retained in STEM, 0 = Not retained in STEM. The University's Institutional Knowledge Management Office provided retention data to the COMPASS staff.

Statistical Analysis/Procedure

As stated earlier, the researcher used Statistical Package for Social Sciences (SPSS, Version 24) to test the six hypotheses for this study using binary logistic regression (Agresti, 2013; Hosmer et al., 2013; Tabachnick & Fidell, 2013). The first step in preparing the data set was to update the existing data file to reflect the most current retention and attrition outcomes for participants. Preliminary analysis of the data included identifying univariate and multivariate outliers and conducting a missing data analysis. Based on the findings of these preliminary procedures, the researcher determined that imputation of missing values was necessary and employed an Expectation Maximization procedure (Dempster, Laird, & Rubin, 1977; Little & Rubin, 2002; Tabachnick & Fidell, 2013); additionally, the researcher removed 16 univariate and multivariate outliers from the dataset. The assumptions for logistic regression include (a) checking the ratio of cases to predictor variables, (b) verifying a linear relationship between the logit transform of the dependent variable and continuous predictors, (c) checking for multicollinearity, and (d) examining potential outliers in the solution (Tabachnick & Fidell, 2013). The only assumption that required additional attention related to the number of

participants from the Asian/Pacific Islander and Other sub-categories of the ethnicity variable within each of the retention outcomes. However, due to the researcher's desire to keep the ethnicity variable in-tact versus collapsing and dummy coding this variable, the ethnicity variable was left as is.

With each hypothesis, the researcher opened the Binary Logistic Regression procedure within SPSS. The first step was to select the appropriate categorical dependent variable for each hypothesis, as well as the independent variables used as predictors (see the following paragraphs for specific variables used in each hypothesis). Categorical predictors were identified as such using the Categorical Covariates function; the researcher indicated which subgroup to use as the reference category for each categorical predictor. Using the Options function, the researcher opted to obtain the Classification plots, the Hosmer-Lemeshow Goodness of Fit test, the Casewise listing of residuals, the 95 percent Confidence Intervals for the Odds Ratios, the standardized and unstandardized residual statistics and the Cook's d values. The researcher used each of these values to evaluate various aspects of the model.

To analyze hypotheses one through three, the researcher utilized Year 2 STEM retention as the outcome variable to examine the influence of variables on retention in STEM from the first year to the second year. The analysis for Hypothesis one utilized cases from both the Career Planning group and the STEM Seminar group and initially included all 10 independent variables. The analysis for hypothesis two utilized only the cases from the Career Planning group; as such, the STEM Course participation variable was removed from the model, leaving nine independent variables. In contrast, the analysis for Hypothesis three utilized only the cases from the STEM

Seminar group; the STEM Course participation variable was also removed from this model, leaving nine independent variables.

To analyze hypotheses four through six, the researcher utilized Year 3 STEM retention as the outcome variable to examine the influence of variables on retention in STEM from the first year to the third year. The analysis for Hypothesis four utilized cases from both the Career Planning group and the STEM Seminar group and was tested using all 10 independent variables. The analysis for Hypothesis five utilized only the cases from the Career Planning group; as with Hypotheses two and three, the STEM Course participation variable was removed from the model, leaving nine independent variables. Finally, the analysis for Hypothesis six utilized only the cases from the STEM Seminar group; the STEM Course participation variable was also removed from this model, leaving nine independent variables.

Ethical Considerations

The current study was part of a larger grant-funded research project that the University's Institutional Review Board had already been approved. As such, this study was in line with the parameters of the larger study. Participants had already provided informed consent for their information to be used within the study and were aware that participation is voluntary and that they could have withdrawn from the study at any time. Prior to beginning the study, the researcher obtained the permission and approval of the dissertation chair, the dissertation committee, and the COMPASS Project Director.

Summary

The researcher conducted the current study as part of a larger grant-funded research project aiming at increasing undergraduate participation and retention in STEM majors. The purpose of this proposed study was to investigate whether demographics, math ability, and career development factors could predict undergraduate retention in STEM majors in the first two years of college. The goal of the study was to advance the literature related to STEM retention, particularly in the area of career development as predictor and factor.

Because the dependent variables are dichotomous and categorical, the researcher used binary logistic regression to analyze the data and to build a potentially predictive model. the researcher used the following as independent variables for the study: (a) gender, (b) ethnicity, (c) initial major, (d) career development participation, (e) Career Thoughts Inventory change scores, (f) SAT Math scores, and (g) UCF Math Placement Test scores. The two dependent variables that the researcher tested separately were Year Two STEM retention and Year Three STEM retention. Constructing a parsimonious predictive model was useful for purposes of research, undergraduate advising and programming, post-secondary career development programming, and counselor education.

CHAPTER IV: RESULTS

Introduction

Science, technology, engineering, and mathematics (STEM) fields face projected deficits in the number of qualified workers to fill new jobs and vacancies (National Science Foundation [NSF], 2013; National Academy of Sciences [NAS], 2011; Xue & Larson, 2015). Carnevale, Smith, and Melton (2011) identified attrition rates for undergraduates in STEM majors as one contributor to the crisis facing STEM fields. In a longitudinal analysis of approximately 7,800 first year undergraduates from a national sample, Chen (2013) reported that less than 30 percent of these students chose a STEM major; furthermore, approximately half of these students left their STEM majors prior to graduating. Researchers have previously investigated associations between retention in STEM majors and gender, ethnicity, and math related variables; however, they have overlooked associations between retention in STEM majors and career development factors, particularly measures of career readiness and participation in a career intervention.

The purpose of the present study was to investigate the degree to which ethnicity, gender, initial major, Math Placement--Algebra Test scores, SAT Math scores, participation in a career planning course, and changes in total and subscale scores on the Career Thoughts Inventory could predict retention in STEM majors. In this chapter, the researcher presents the statistical results of the analyses used within the study. First, the researcher reintroduces the research hypotheses tested within the study. The next section addresses preliminary analyses for logistic regression, including missing values analysis, outlier identification, and assumptions testing. Then the researcher presents results associated with each hypothesis. As the hypotheses are organized by dependent variable (i.e., $H0_1$-$H0_3$ for 2nd Year STEM Retention and $H0_4$-$H0_6$ for 3rd

Year STEM Retention), the researcher presents a summary for each group of hypotheses, as well as an overall summary at the end of this chapter.

Research Hypotheses

Null Hypothesis 1: First-year to second-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, STEM Course Participation (Career Planning vs. STEM Seminar), and CTI change scores.

Null Hypothesis 2: First-year to second-year undergraduate retention in STEM majors for students participating in a STEM-focused Career Planning Course cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 3: First-year to second-year undergraduate retention in STEM majors for students participating in a STEM Seminar Course (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 4: First-year to third-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test

scores, SAT Math scores, STEM Course Participation (Career Planning vs. STEM Seminar), and CTI change scores.

Null Hypothesis 5: First-year to third-year undergraduate retention in STEM majors for students participating in a STEM-focused Career Planning Course cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 6: First-year to third-year undergraduate retention in STEM majors for students participating in a STEM Seminar Course (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Preliminary Analyses

To investigate the six hypotheses, the researcher used a binary logistic regression as the primary data analysis procedure. Prior to running this procedure, the researcher ran preliminary analyses, including examining the data set for missing values, identifying univariate and multivariate outliers, and testing the assumptions of logistic regression. Testing these preliminary analyses safeguards the integrity of the analysis and helps the researcher identify any corrections or transformations the researcher may need to make with the data (Tabachnick & Fidell, 2013). In this section, the researcher presents results of these analyses with implications for the present study before presenting descriptive statistics for the dataset.

Missing Values Analysis

The researcher examined each dependent and independent variable used in the study for missing values. There were no missing values for either of the outcome variables or for participants' gender, ethnicity, or initial major, as the University's Institutional Knowledge Management Office provided these data points for all participants. Moreover, the Career Planning variable that identified whether students took the Career Planning class or the STEM Seminar class was also complete. Missing values existed for the SAT Mathematics scores, the UCF Math Placement Test--Algebra scores, and the pre and post-administration of the Career Thoughts Inventory (Total score and three subscales). Table 1 describes the missing data for these variables.

Table 1. Missing Data for Continuous Variables

	Complete	*Missing*	*% Missing*	*Mean*	*SD*
SAT Math	374	55	12.8	625.13	60.82
Math Placement Algebra	316	113	26.3	305.78	95.25
CTI DMC Pre	417	12	2.8	11.04	7.39
CTI CA Pre	417	12	2.8	15.55	7.60
CTI EC Pre	415	14	3.3	3.98	3.07
CTI Total Pre	415	14	3.3	48.80	20.58
CTI DMC Post	359	70	16.3	7.10	7.24
CTI CA Post	359	70	16.3	12.21	7.38
CTI EC Post	359	70	16.3	3.45	6.96
CTI Total Post	359	70	16.3	34.67	21.63

The Missing Values Analysis revealed that missing data was most problematic for the SAT Math and Math Placement--Algebra scores, as well as the post-administration of the CTI. Values for the SAT Math test were missing due to some students taking the ACT rather than the SAT as a college admissions test. The Math Placement Test was not a requirement for all first-year students when the COMPASS Program started, and some students elected not to take the Math Placement Test due to receiving college math credits through other programs (e.g. Advanced Placement, dual enrollment). Attrition between the pre and post administration was a problem for the CTI, with the percentage of missing cases increasing from 2.8 percent to 16.3 percent for the DMC and CA subscales and from 3.3 percent to 16.3 percent for the EC subscale and the Total score. These increases in the number of missing CTI scores may be due to students being absent from either the STEM-focused Career Planning course or the STEM Seminar course on the day the CTI post-test was administered or students withdrawing from either course.

The researcher used Little's MCAR test in SPSS to determine whether missing cases were missing completely at random (Little, 1988). Results from the test indicated that the data were not missing completely at random (Chi-square = 839.606, df = 161, $p < .001$). The missingness for SAT Math, Math Placement--Algebra, and the CTI Post were predictable based on the outcome variable but did have a relationship to other variables. Therefore, the researcher determined them to be missing at random (MAR) and chose to impute missing values rather than deletion, as deletion could skew or bias the data set (Little, 1988; Little & Rubin, 2002).

To impute missing values, the researcher used the Expectation Maximization (EM) procedure within SPSS's Missing Values Analysis function, which is appropriate for MAR data (Tabachnick & Fidell, 2013). The EM procedure used a two-step process to impute values (Demptster, Laird, & Rubin, 1977; Little & Rubin, 2002). In the first step, the procedure

estimated the means, variances, and covariances for the variables of interest based on the complete cases. In the second step, EM used a maximum likelihood procedure to estimate regression equations for the variables of interest based on the calculations from the first step; SPSS generated the missing values using these regression equations (Tabachnick & Fidell, 2013). The researcher incorporated the generated values into the existing data file.

Univariate & Multivariate Outliers

Next, the researcher tested for univariate outliers within the continuous variables. For continuous variables, univariate outliers were cases that had standardized scores with an absolute value higher than 3.29 (Tabachnick and Fidell, 2013). The Math Placement--Algebra variable had no identified univariate outliers, the SAT Math and CTI Total Change variables each had one univariate outlier, and the CTI CA Change and CTI EC Change variables each had two univariate outliers. The CTI DMC Change variable had six identified univariate outliers. In all, there were 10 univariate outliers, as one case was considered an outlier for three different variables (See Table 13). Based on the recommendation of Field (2009) and Tabachnick and Fidell (2013), the researcher excluded these cases from the analysis.

Table 2. Univariate Outliers for Continuous Variables

Variable	*Case number*
SAT Math	836
MP_Algebra	none
CTI Total Change	291
CTI DMC Change	291, 292, 329, 339, 1094, 1060
CTI CA Change	291, 952
CTI EC Change	101, 590

In addition to univariate outliers, the researcher also tested the dataset for multivariate outliers using the Mahalanobis distance. The Mahalanobis distance values represent the distance of each case from the point around which all other cases swarm on the multivariate level (Tabachnick & Fidell, 2013). The researcher computed the Mahalanobis distance for each case using the linear regression function of SPSS and then compared the Mahalanobis distance values for each case to the critical value for 10 predictor variables ($p < .001$) of 29.588. Analysis of these values revealed six potential multivariate outliers (Cases 27, 260, 295, 303, 482, 943), which were excluded from the analyses.

Assumptions Testing for Logistic Regression

Next, the researcher tested the assumptions of logistic regression with the dataset (Field, 2009; Hosmer, Lemeshow, & Sturdivant, 2013; Tabachnick & Fidell, 2013). The first assumption, which related to sample size, required the researcher to determine if an adequate number of cases existed for each categorical independent variable in each outcome of the dependent variable (i.e. an adequate representation for each categorical variable in both the retained group and the not retained group). Peduzzi, Concato, Kemper, Holford, and Feinstein (1996) recommended that each outcome have at least 10 cases for each predictor; however, Field (2009) and Vittinghof and McCulloch (2006) both recommended that the minimum number of cases per outcome for each predictor could be as low as 5.

Within the data set, all continuous variables and all categorical variables sufficiently met both the 10 case recommendation by Peduzzi et al. (1996) and the 5 case recommendation by Field (2009) except the non-retained Asian/Pacific Islander and Other subcategories of the categorical Ethnicity variable. For the analysis of first year retention (Hypotheses 1 through 3),

the Asian/Pacific Islander subcategory only had 4 cases in the non-retained outcome, which violated the Peduzzi et al. (1996) and Field (2009) recommendations. The Other subcategory had 5 cases in the non-retained outcome, which violated the Peduzzi et al. recommendation but meets the Field recommendation. For the analysis of second year retention (Hypotheses 4 through 6), the Asian/Pacific Islander and Other subcategories both had 5 cases. Hosmer et al. (2013) cautioned that an insufficient number of cases in each outcome may lead to overfitting or underfitting the model; however, they also added that the 10 case and 5 case recommendations should be considered a guideline rather than a strict rule and that researchers should make the final determination. One possible solution would have been to collapse the Ethnicity variable into fewer subcategories (e.g. White/non-White, minority in STEM/non-minority in STEM). However, the researcher kept the existing categories to allow for viewing of the subcategories disaggregated, while noting the possibility of over/underfitting the model as a potential limitation.

In regression analyses, multicollinearity among the predictor variables can inhibit the researcher's ability to assess the individual importance of each predictor (Field, 2009; Tabachnick & Fidell, 2013). To test for multicollinearity, the researcher ran the model as a linear regression to obtain the collinearity diagnostics (Field, 2009; Pallant, 2013). Menard (1995) posited that tolerance values less than 0.1 are indicative of collinearity issues. None of the predictor variables in this data set violated this assumption for either of the outcome variables (2nd year STEM retention or 3rd year STEM retention). Myers (1990) specified that variance inflation factor (VIF) values greater than 10 are indicative of multicollinearity issues. None of the predictor variables violated this rule for either outcome variable. Table 12 displays collinearity statistics (Tolerance values and Variance Inflation Factor values) for each of the

predictor variables for each of the dependent variables (2nd year STEM retention and 3rd year STEM retention).

Table 3. Multicollinearity Statistics

	DV: 2nd Year Retention		*DV: 3rd Year Retention*	
Predictor	*Tolerance*	*VIF*	*Tolerance*	*VIF*
Gender	.882	1.134	.893	1.120
Ethnicity	.975	1.025	.971	1.030
Career Planning Participation	.891	1.123	.899	1.112
Initial Major	.932	1.073	.922	1.085
SAT Math	.748	1.337	.707	1.415
Math Placement-Algebra	.774	1.292	.744	1.343
CTI Total Change	.407	2.457	.341	2.930
CTI DMC Change	.527	1.897	.523	1.911
CTI CA Change	.705	1.417	.571	1.751
CTI EC Change	.686	1.458	.685	1.461

Logistic regression also operates with the assumption that a linear relationship exists between the continuous predictors and the logit transformation of the dependent variable (Field, 2009; Hosmer et al., 2013; Tabachnick & Fidell, 2013). The researcher used the Box-Tidwell approach to test this assumption; this approach involved computing the natural logarithm of the continuous variables (SAT Math, Math Placement--Algebra, and CTI Change variables) and then adding interactions between the continuous variables and their natural logarithm as predictors into the full logistic regression model (Hosmer et al., 2013; Tabachnick & Fidell, 2013). None of the interaction terms were statistically significant ($p < .05$), so this assumption was met.

The final assumption of logistic regression required testing for outliers in the solution of the model (Hosmer et al., 2013; Tabachnick & Fidell, 2013). Distinct from univariate and multivariate outliers, outliers in the solution refer to cases for which the model did not fit well, as measured by Cook's distance values above 1.00 or standardized residual values at or above 3.00 (Field, 2009; Tabachnick & Fidell, 2013). After identifying outliers in the solution, the researcher has the option of removing those outlier cases and rerunning the analysis with the goal of increasing precision. As this assumption required the researcher to examine residual statistics for each analysis, outliers in the solution are presented in the section for each hypothesis.

Descriptive Statistics

Descriptive statistics allow the researcher and readers to better understand the sample within the study. Because the study includes two dependent variables that were tested separately, the researcher divided the descriptive statistics for each of the retention outcome variables.

Descriptive Statistics for Year 2 STEM Retention

Table 4 displays descriptive statistics for the categorical variables used in the analyses for Hypotheses 1 through 3 (evaluating Year 1 to Year 2 STEM retention); the table shows the statistics for the entire data set and for each of the retention outcomes (retained or not retained). The sample overall was nearly half female, which was a larger representation of females than STEM fields overall and previous studies examining gender in STEM; the high number of females likely was due to the COMPASS Program's attention to gender issues in STEM. More females were in the retained group than the non-retained group, but females represented a larger

proportion of the non-retained group. Regarding ethnicity, more than half of the sample consists of Caucasian/White students, which is representatives of the University and STEM overall. A larger number of students were in the Career Planning group than the STEM Seminar group. Similarly, a larger number of students were in the Undeclared Initial Major group.

Table 4. Descriptive Statistics for Categorical Variables (2nd Year STEM Retention)

Variable	Retained		Not Retained		Total	
	n	%[a]	*n*	%[b]	*n*	%[c]
Gender						
Male	159	58.9	74	46.5	233	54.3
Female	111	41.1	85	53.5	196	45.7
Total	270	100.0	159	100.0	429	100.0
Ethnicity						
Caucasian/White	147	54.4	100	62.9	247	57.6
African American/Black	31	11.5	16	10.1	47	11.0
Hispanic	57	21.1	34	21.4	91	21.2
Asian/Pacific Islander	24	8.9	4	2.5	28	6.5
Other	11	4.1	5	3.1	16	3.7
Total	270	100.0	159	100.0	429	100.0
Course						
Career Planning	137	50.7	120	75.5	257	59.9
STEM Seminar	133	49.3	39	24.5	172	40.1
Total	270	100.0	159	100.0	429	100.0
Initial Major						
Undeclared	130	48.1	72	45.3	202	47.1
STEM	124	45.9	40	25.2	164	38.2
Non-STEM	16	5.9	47	29.6	63	14.7
Total	270	100.0	159	100.0	429	100.0

Note. a = percentage of the Retained group. b = percentage of the Not Retained group. c = percentage of the Total group.

Tables 5 through 8 provide descriptive statistics for all continuous variables that the researcher used to analyze Hypotheses 1 through 3 (testing first to second year STEM retention). Table 5 displays the means, standard deviations, and ranges for the SAT Mathematics and Math Placement Algebra subtest, including the data for the entire sample and the two retention outcome groups (retained and not retained). The Retained group had higher mean scores on both the SAT Math test and the UCF Math Placement-Algebra test. The minimum scores for the SAT Math test were below the 550 required for admission to the COMPASS Program, which resulted from the Expectation Maximization procedure for imputing missing values (i.e., the cases with scores below 550 were missing the SAT Math score prior to the Missing Values Analysis.

Table 5. Descriptive Statistics for Math Variables (2nd Year STEM Retention)

Variables	*Mean*	*SD*	*Minimum*	*Maximum*
SAT Mathematics				
Retained	631.61	56.74	470.00	800.00
Non-Retained	614.07	56.57	390.00	770.00
Total	625.11	57.24	390.00	800.00
Math Placement--Algebra				
Retained	313.89	88.99	40.00	500.00
Non-Retained	285.37	72.41	80.00	480.00
Total	303.32	84.28	40.00	500.00

Note. Total *N* for 2nd Year Retention = 429; Retained *n* = 270, Non-Retained *n* = 159).

Table 6 displays the means, standard deviations, and ranges for the CTI Pretest Total and subscales, including the data for the entire sample and the two retention outcomes. The Non-Retained group had higher mean scores on the pretest CTI Total and all three subscales,

indicating that the students who were not retained in a STEM major initially had slightly higher negative career thoughts than the students who were eventually retained in a STEM major.

Table 6. Descriptive Statistics for CTI Pretest Variables (2nd Year STEM Retention)

Variables	*Mean*	*SD*	*Minimum*	*Maximum*
CTI Total Pretest				
Retained	48.49	20.48	0.00	110.00
Non-Retained	49.13	20.10	3.00	97.00
Total	48.73	20.32	0.00	110.00
CTI DMC Pretest				
Retained	10.76	7.47	0.00	34.00
Non-Retained	11.57	7.02	0.00	31.00
Total	11.06	7.30	0.00	34.00
CTI CA Pretest				
Retained	14.69	5.58	0.00	25.00
Non-Retained	16.15	6.80	2.00	59.00
Total	15.23	6.09	0.00	59.00
CTI EC Pretest				
Retained	3.86	2.64	0.00	13.00
Non-Retained	3.94	2.62	0.00	10.00
Total	3.89	2.63	0.00	13.00

Note. Total N for 2nd Year Retention = 429; Retained n = 270, Non-Retained n = 159).

Table 7 displays the descriptive statistics for the CTI Posttest Total and subscales in the same format as Table 6. The Non-Retained group had higher mean scores on the posttest CTI Total and all three subscales, indicating that the students who were not retained in a STEM major

still had higher negative career thoughts after the first semester of college than the students who were eventually retained in a STEM major.

Table 7. Descriptive Statistics for CTI Posttest Variables (2nd Year STEM Retention)

Variables	*Mean*	*SD*	*Minimum*	*Maximum*
CTI Total Posttest				
Retained	33.14	20.30	0.00	93.00
Non-Retained	37.61	21.08	0.00	11.00
Total	34.80	20.68	0.00	99.00
CTI DMC Posttest				
Retained	6.52	6.61	0.00	26.00
Non-Retained	8.20	7.25	0.00	32.00
Total	7.14	6.89	0.00	34.00
CTI CA Posttest				
Retained	11.32	6.16	0.00	26.00
Non-Retained	12.84	5.80	0.00	25.00
Total	11.89	6.07	0.00	26.00
CTI EC Posttest				
Retained	2.72	2.67	0.00	15.00
Non-Retained	3.07	2.53	0.00	11.00
Total	2.85	2.62	0.00	15.00

Note. Total *N* for 2nd Year Retention = 429; Retained *n* = 270, Non-Retained *n* = 159).

Table 8 displays the descriptive statistics for the CTI Change Score variables, which the researcher calculated by finding the mathematical difference between the pretest and posttest administrations of the CTI. The Retained group had higher mean change scores for the CTI

Total and all three subscales, indicating that the Retained group showed larger decreases in negative career thinking than the Non-Retained group.

Table 8. Descriptive Statistics for CTI Change Variables (2nd Year STEM Retention)

	Retained		Non-Retained		Total	
Variables	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
CTI Total Change	15.35	16.86	11.53	20.60	13.93	18.41
CTI DMC Change	4.24	5.91	3.37	6.15	3.92	6.01
CTI CA Change	3.37	5.08	3.31	6.52	3.34	5.65
CTI EC Change	1.14	2.89	.87	2.76	1.04	2.84

Note. Total *N* for 2nd Year Retention = 429; Retained *n* = 270, Non-Retained *n* = 159).

Descriptive Statistics for Year 3 STEM Retention

Because fewer students had made it to their third year of college than to their second year of college at the time of the data analysis, the sample for Hypotheses 4 through 6 was smaller than the sample for Hypotheses 1 through 3. As such, the researcher provided descriptive statistics separately for the second dependent variable (evaluating Year 1 to Year 3 STEM retention). Table 9 displays descriptive statistics for the categorical variables used in the analysis for Hypotheses 4 through 6; as with Table 4, this table includes statistics for the entire sample and for each of the retention outcomes (retained or not retained). The sample overall was half female, which was a larger representation of females than STEM fields overall and previous studies examining gender in STEM. More females were in the non-retained group. Regarding ethnicity, more than half of the sample consists of Caucasian/White students, which is representatives of the University and STEM overall. A larger number of students were in the

Career Planning group than the STEM Seminar group. Similarly, a larger number of students were in the Undeclared Initial Major group.

Table 9. Descriptive Statistics for Categorical Variables (3rd Year STEM Retention)

Variable	Retained		Not Retained		Total	
	n	%[a]	*n*	%[b]	*n*	%[c]
Gender						
Male	72	55.8	65	44.8	137	50.0
Female	57	44.2	80	55.2	137	50.0
Total	129	100.0	145	100.0	274	100.0
Ethnicity						
Caucasian/White	66	51.2	85	58.6	151	55.1
African American/Black	16	12.4	18	12.4	34	12.4
Hispanic	29	22.5	32	22.1	61	22.3
Asian/Pacific Islander	10	7.8	5	3.4	15	5.5
Other	8	6.2	5	3.4	13	4.7
Total	129	100.0	145	100.0	274	100.0
Course						
Career Planning	76	58.9	112	77.2	188	68.6
STEM Seminar	53	41.1	33	22.8	86	31.4
Total	129	100.0	145	100.0	274	100.0
Initial Major						
Undeclared	65	50.4	63	43.4	128	46.7
STEM	55	42.6	39	26.9	94	34.3
Non-STEM	9	7.0	43	29.7	52	19.0
Total	129	100	145	100	274	100.0

Note. a = percentage of the Retained group. b = percentage of the Not Retained group. c = percentage of the Total group.

Tables 10 through 13 provide descriptive statistics for all continuous variables that the researcher used to analyze Hypotheses 4 through 6 (testing first to third year STEM retention). Table 10 displays the means, standard deviations, and ranges for the SAT Mathematics and Math Placement Algebra subtest, including the data for the entire sample and the two retention outcome groups (retained and not retained). The Retained group had higher mean scores on both the SAT Math test and the UCF Math Placement-Algebra test. The minimum scores for the SAT Math test were below the 550 required for admission to the COMPASS Program, which resulted from the Expectation Maximization procedure for imputing missing values (i.e., the cases with scores below 550 were missing the SAT Math score prior to the Missing Values Analysis.

Table 10. Descriptive Statistics for Math Variables (3rd Year STEM Retention)

Variables	*Mean*	*SD*	*Minimum*	*Maximum*
SAT Mathematics				
Retained	636.89	57.27	530.00	800.00
Non-Retained	614.01	57.37	440.00	770.00
Total	624.78	58.35	440.00	800.00
Math Placement--Algebra				
Retained	323.39	85.83	80.00	500.00
Non-Retained	282.65	77.41	80.00	480.00
Total	301.83	83.84	80.00	500.00

Note. Total *N* for 3rd Year Retention = 274; Retained *n* = 129, Non-Retained *n* = 145).

Table 11 displays the means, standard deviations, and ranges for the CTI Pretest Total and subscales, including the data for the entire sample and the two retention outcomes. The Non-Retained group had higher mean scores on the pretest CTI Total and all three subscales,

indicating that the students who were not retained in a STEM major initially had slightly higher negative career thoughts than the students who were eventually retained in a STEM major.

Table 11. Descriptive Statistics for CTI Pretest Variables (3rd Year STEM Retention)

Variables	*Mean*	*SD*	*Minimum*	*Maximum*
CTI Total Pretest				
Retained	46.40	20.68	0.00	110.00
Non-Retained	50.62	20.21	3.00	94.00
Total	48.64	20.50	0.00	110.00
CTI DMC Pretest				
Retained	10.37	7.53	0.00	34.00
Non-Retained	11.95	7.01	0.00	28.00
Total	11.21	7.29	0.00	34.00
CTI CA Pretest				
Retained	14.51	5.78	0.00	24.00
Non-Retained	16.37	5.83	0.00	28.00
Total	15.50	5.87	0.00	28.00
CTI EC Pretest				
Retained	3.70	2.73	0.00	12.00
Non-Retained	4.07	2.63	0.00	11.00
Total	3.90	2.68	0.00	12.00

Note. Total *N* for 3rd Year Retention = 274; Retained *n* = 129, Non-Retained *n* = 145).

Table 12 displays the descriptive statistics for the CTI Posttest Total and subscales in the same format as Table 11. The Non-Retained group had higher mean scores on the posttest CTI Total and all three subscales, indicating that the students who were not retained in a STEM major

initially still had higher negative career thoughts after the first semester of college than the students who were eventually retained in a STEM major.

Table 12. Descriptive Statistics for CTI Posttest Variables (3rd Year STEM Retention)

Variables	*Mean*	*SD*	*Minimum*	*Maximum*
CTI Total Posttest				
Retained	32.47	20.92	0.00	99.00
Non-Retained	35.57	20.48	0.00	83.00
Total	34.11	20.71	0.00	99.00
CTI DMC Posttest				
Retained	6.38	6.51	0.00	28.00
Non-Retained	7.64	6.99	0.00	30.00
Total	7.05	6.79	0.00	30.00
CTI CA Posttest				
Retained	11.43	6.26	0.00	26.00
Non-Retained	12.61	6.09	0.00	25.00
Total	12.05	6.19	0.00	26.00
CTI EC Posttest				
Retained	2.77	2.72	0.00	12.00
Non-Retained	3.16	2.94	0.00	15.00
Total	2.98	2.84	0.00	15.00

Note. Total *N* for 3rd Year Retention = 274; Retained *n* = 129, Non-Retained *n* = 145).

Table 13 displays the descriptive statistics for the CTI Change Score variables, which the researcher calculated by finding the mathematical difference between the pretest and posttest administrations of the CTI. The Non-Retained group had higher mean change scores for the CTI Total and all subscales except the External Conflict subscale. These statistics indicate that the

Non-Retained group showed larger decreases in negative career thinking than the Retained group, except with External Conflict.

Table 13. Descriptive Statistics for CTI Change Variables (3rd Year STEM Retention)

	Retained		Non-Retained		Total	
Variables	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
CTI Total Change	13.93	17.77	15.06	20.34	14.53	19.15
CTI DMC Change	3.98	6.21	4.32	6.16	4.16	6.18
CTI CA Change	3.09	5.39	3.76	5.46	3.44	5.43
CTI EC Change	.93	2.98	.91	3.15	.92	3.07

Note. Total *N* for 3rd Year Retention = 274; Retained *n* = 129, Non-Retained *n* = 145).

Results of Data Analyses

Hypothesis 1

To test the first null hypothesis, which stated that first-year STEM undergraduate retention could not be predicted by the independent variables, the researcher ran a binary logistic regression with 2nd Year STEM Retention as the binary outcome variable. Categorical predictor variables included Gender (Male = 0, Female = 1), Ethnicity (Caucasian/White = 1, African American/Black = 2, Hispanic = 3, Asian/Pacific Islander = 4, Other = 5), Initial Major (Undeclared = 1, Declared STEM = 2, Declared Non-STEM = 3), and Career Planning Participation (Career Planning = 1, STEM Seminar = 2). A previous researcher established the coding scheme for some of these variables, and SPSS automatically dummy coded identified categorical variables with more than two categories. Continuous variables included SAT Math scores, Math Placement--Algebra Test scores, CTI Total Change scores, CTI DMC Change

Scores, CTI CA Change Scores, and CTI EC Change Scores. The sample for this analysis included 413 cases after removing the univariate and multivariate outliers. The researcher used a Backward (Stepwise) Wald procedure for including variables in the model. In this procedure, the analysis initially included all predictor variables; variables with *p* values higher than a designated cutoff point were removed one by one until only variables with *p* values at or below the cutoff points remained in the model (Hosmer et al., 2013; Tabachnick & Fidell, 2013). SPSS defaults to an alpha level of .05, but Hosmer et al. (2013) recommend a more liberal cutoff point between .15 and .20. For this analysis, the researcher used a cutoff point of .20 for a predictor to be included in the model; using a higher cutoff point helped address the possibility of a stepwise approach removing a variable that still contributes to the model without having traditional statistical significance.

The logistic regression required five steps to achieve the most parsimonious model. In the first step, which included all predictor variables, the Chi-square value was 92.445 ($df = 14$, $p < .001$) and the -2 Log likelihood statistic was 452.054. The initial model with all predictors had a Cox & Snell R Square value of .201 and a Nagelkerke R Square statistic of .274, indicating that the model with all predictors explained between 20 and 27 percent of the variance in the outcome. Hosmer et al. (2013) noted that R squared values for logistic regression tend to be lower than linear regression. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model fit well with the data (Chi-square = 6.545, $df = 8$, $p = .586$) because of a non-significant *p* value.

After removing four variables with *p* values greater than .20 (CTI CA Change, CTI EC Change, Gender, CTI DMC Change, respectively) one by one, the Chi-square value for the final model was 91.011 ($df = 10$, $p < .001$). The final model yielded a -2 Log likelihood of 453.488, a

Cox & Snell R Square value of .198, and a Nagelkerke R Square value of .270. These R-Square values showed that the model explained between 20 and 27 percent of the variance in the outcome. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model had a good fit (Chi-square = 6.273, $df = 8$, $p = .617$); a non-significant p value greater than .05 indicated support for the model (Tabachnick & Fidell, 2013).

Table 14 displays a comparison of the observed outcomes and the predicted outcomes. The final model was able to accurately predict 73.4 percent of cases, with most of the accurate predictions being in the retained group. The model predicted approximately 90 percent of the retained students accurately, but predicted the non-retained cases accurately less than half of the time.

Table 14. Classification Table For Hypothesis 1

Observed 2nd Year STEM Retention	Predicted 2nd Year STEM Retention		
	No	Yes	% Correct
No	70	83	45.8
Yes	27	233	89.6
Overall Percentage			73.4

a. The cut value is .500

The final model included the following six variables that met the criteria of having a p value at or below .20 based on the Hosmer et al. (2013) recommendation: Ethnicity, Initial Major, STEM Course Participation, SAT Math, Math Placement--Algebra, and CTI Total Change. Table 15 explains the contributions of each of these variables to the final model, including their observed significance, odds ratio, and 95 percent confidence intervals for the

odds ratios. The odds ratio represents the association between an independent variable and a particular outcome (Hosmer et al., 2013). For this study, the odds ratio represents the extent to which the independent variables predict membership in the STEM retained group. With categorical variables, the odds ratio indicates the likelihood that being in a particular category (e.g. African American) predicts membership in the STEM retained group. With continuous variables, the odds ratio indicates the likelihood that increases or decreases in the independent variable (e.g. SAT Math scores) predict membership in the STEM retained group. Odds ratios can be used as a measure of effect size in that odds ratios closer to 1.0 have a smaller effect (Tabachnick & Fidell, 2013); however, the researcher also converted the odds ratios to eta-squared values as another method of interpreting effect size (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

Table 15. Variables in the Equation for Hypothesis 1

							95% C.I. for O.R.	
Variable	*B*	*S.E.*	*Wald*	*df*	*p value*	*O.R.*	*Lower*	*Upper*
Ethnicity			10.319	4	.035			
Ethnicity (AfricanAmerican/Black)	.576	.393	2.148	1	.143	1.779	.823	3.842
Ethnicity (Hispanic)	.068	.290	.054	1	.816	1.070	.606	1.889
Ethnicity (Asian/Pacific Islander)	1.889	.637	8.803	1	.003	6.615	1.899	23.041
Ethnicity (Other)	.258	.714	.131	1	.717	1.295	.320	5.246
Initial Major			35.824	2	< .001			
Initial Major (Declared STEM)	.412	.265	2.422	1	.120	1.511	.899	2.539
Initial Major (Declared non-STEM)	-1.944	.375	26.905	1	< .001	.143	.069	.298
STEM Seminar (Non-CP)	.850	.258	10.885	1	.001	2.340	1.412	3.879
SAT Math	.004	.002	2.411	1	.120	1.004	.999	1.008
Math Placement--Algebra	.002	.002	2.080	1	.149	1.002	.999	1.005
CTI Total Change	.017	.007	5.546	1	.019	1.017	1.003	1.032
Constant	-2.994	1.378	4.717	1	.030	.050		

Note: O.R. = Odds Ratio

The Wald Chi-square test within logistic regression helps determine the significance of the coefficient for each predictor in the model by dividing the squared coefficient for each variable by its squared standard error (Tabachnick & Fidell, 2013). Based on the results of the Wald test, Initial Major was the most statistically significant predictor ($p < .001$). The odds ratios indicated that participants from the Declared STEM group had a 1.5 times higher likelihood of being in the retained outcome group (eta squared = .01). However, for participants in the Declared non-STEM category, the odds of participants in this group being in the retained outcome group decrease by a factor of .143 (eta squared = .22). With a similar significance level ($p = .001$), the students in the STEM Seminar group (i.e. the students who did not take the career planning class) had a 2.34 times higher likelihood of being in the retained group (eta squared = .05). The CTI Total change variable was also a statistically significant predictor at the .05 level; the odds ratio for this variable indicates that for every unit increase in CTI Total Change score, the odds of being in the retained group are 1.017 times higher (eta squared < .001). Ethnicity was another predictor variable that was a significant predictor at the .05 level. All of the categories had odds ratios above 1, indicating that the African American/Black, Hispanic, Asian/Pacific Islander, and Other subgroups all had higher odds of being in the retained group than the reference category of Caucasian/White students. However, the wide confidence interval range and the high odds ratio may, particularly with the Asian/Pacific Islander and Other subgroups, result from the small number of cases in both outcome groups for the subgroups.

Both the SAT Math and Math Placement--Algebra tests were not statistically significant at the .05 level but met the Hosmer et al. (2013) recommendation for acceptable alpha levels. Because the 95 percent confidence interval range contains the value of 1.00, the researcher cannot rule out the possibility that the true odds ratio is 1.00, which would indicate that this

variable predicts an equal probability of a case being in either the retained or non-retained outcome. Despite not having statistical significance at the .05 level, these variables may have contributed to the overall model and increased precision with other variables.

Examining the residual statistics for each case helped evaluate goodness of fit and identify outliers for which the model did not fit (Tabachnick & Fidell, 2013). Cook's distance measures the effect of deleting a particular case from the model; cases with high Cook's distance values should be evaluated further (Field, 2009). There were no unusually high Cook's distance values, as all were below 1.00 (Field, 2009). SPSS determined residual values by calculating the difference between the predicted outcome (i.e. a value between 0 and 1) and the observed value (i.e. a value of 0 or 1); after standardizing the residual value, the researcher could identify outliers in the solution by finding cases with a standardized residual value at or above 3.00 (Field, 2009; Tabachnick & Fidell, 2013). Table 16 displays four cases that met this criterion. Upon further inspection of these individual cases, the only trends the researcher observed were that three of the four were in the Asian/Pacific Islander subgroup and three of the four were in the non-retained outcome group. This finding may indicate that the model did not work well for participants who are in both the Asian/Pacific Islander subgroup and the non-retained group; however, due to the small number of participants who met both of these criteria ($n = 5$), the researcher could not conclusively determine this. Eliminating these cases may have improved the model fit, but it would also have resulted in a subgroup (non-retained Asian/Pacific Islander students) with only two cases; as such, the researcher chose to keep them in the analysis to avoid having to collapse the Ethnicity variable into fewer categories (i.e. minority/non-minority).

Table 16. Outliers in the Solution for Hypothesis 1

Case No.	Observed First Year STEM Retention	Predicted	Predicted Group	Resid	ZResid
855	Y	.064	N	.936	3.816
860	N	.921	Y	-.921	-3.416
910	N	.953	Y	-.953	-4.518
1421	N	.978	Y	-.978	-6.631

In summary, adding the predictors into the logistic regression model did improve the predictions made. Removing predictors with *p* values greater than .20 did increase the model fit based on the Hosmer and Lemeshow test, but slightly decreased the variance accounted for by the model, as measured by a decreased Chi-square statistic and an increased -2 Log likelihood statistic. Despite these differences, the R-squared values minimally changed with the removal of more highly non-significant predictors. The Initial Major variable, the STEM Course variable, and the Ethnicity variable were the most significant predictors in the final model, although the math variables and the CTI Total change variable contributed. Overall, the model performed well in predicting retained students but only predicted non-retained students correctly with less than half of cases.

Hypothesis 2

To test the second hypothesis, which stated that 2nd year undergraduate retention in STEM majors could not be predicted by the independent variables for students in a STEM-focused career planning class, the researcher ran a binary logistic regression with 2nd Year STEM Retention as the binary outcome variable. Categorical predictor variables included

Gender (Male = 0, Female = 1), Ethnicity (Caucasian/White = 1, African American/Black = 2, Hispanic = 3, Asian/Pacific Islander = 4, Other = 5), and Initial Major (Undeclared = 1, Declared STEM = 2, Declared Non-STEM = 3). A previous researcher established the coding scheme for some of these variables, and SPSS automatically dummy coded identified categorical variables with more than two categories. Continuous variables included SAT Math scores, Math Placement--Algebra Test scores, CTI Total Change scores, CTI DMC Change Scores, CTI CA Change Scores, and CTI EC Change Scores. The sample for this analysis included 247 cases from the Career Planning group after removing the univariate and multivariate outliers. The researcher used a Backward (Stepwise) Wald procedure for including variables in the model. In this procedure, all the analysis initially included all predictor variables; variables with *p* values higher than a designated cutoff point were removed one by one until only variables with *p* values at or below the cutoff points remained in the model (Hosmer et al., 2013; Tabachnick & Fidell, 2013). For this analysis, the researcher used a cutoff point of .20 for a predictor to be included in the model; using a higher cutoff point helped address the possibility of a stepwise approach removing a variable that still contributes to the model without having traditional statistical significance.

The logistic regression required six steps to achieve the most parsimonious model. In the first step, which included all predictor variables, the Chi-square value was 50.227 ($df = 13$, $p < .001$) and the -2 Log likelihood statistic was 291.277. The initial model with all predictors had a Cox & Snell R Square value of .184 and a Nagelkerke R Square value of .246, indicating that the model with all predictors explained between 18 and 25 percent of the variance in the outcome. Hosmer et al. (2013) noted that R squared values for logistic regression tend to be lower than

linear regression. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model fit well with the data (Chi-square = 9.420, *df* = 8, *p* = .308) because of a non-significant *p* value.

After removing four variables with *p* values greater than .20 (CTI EC Change, CTI CA Change, CTI Total Change, SAT Math, and Gender, respectively) one by one, the Chi-square value for the model was 45.857 (*df* = 8, *p* < .001). The final model yielded a -2 Log likelihood of 295.646, a Cox & Snell R Square value of .169, and a Nagelkerke R Square value of .226. These R-Square values showed that the model explained between 17 and 23 percent of the variance in the outcome. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model had a good fit (Chi-square = 6.441, *df* = 8, *p* = .598); a *p* value greater than .05 indicates support for the model (Tabachnick & Fidell, 2013).

The final model was able to accurately predict 64.8 percent of cases, with most of the accurate predictions being in the retained group. Table 17 displays a comparison of the observed outcomes and the predicted outcomes. The model predicted approximately 80 percent of the retained students accurately, but predicted the non-retained cases accurately less than half of the time.

Table 17. Classification Table for Hypothesis 2

	Predicted Year 1 STEM Retention		
Observed Year 1 STEM Retention	No	Yes	% Correct
No	55	61	47.4
Yes	26	105	80.2
Overall Percentage			64.8

a. The cut value is .500

The final model included the following variables that met the criteria of having a *p* value at or below .20 based on the Hosmer et al. (2013) recommendation: Ethnicity, Initial Major, Math Placement--Algebra, and CTI DMC Change. Table 18 explains the contributions of each of these variables to the final model, including their observed significance, odds ratio and 95 percent confidence intervals for the odds ratios. As a reminder, the odds ratio represents the association between an independent variable and a particular outcome (Hosmer et al., 2013). Specific to this study, the odds ratio represents the extent to which the independent variables predict membership in the STEM retained group. Odds ratios can be used as a measure of effect size in that odds ratios closer to 1.0 have a smaller effect (Tabachnick & Fidell, 2013); however, the researcher also converted the odds ratios to eta-squared values as another method of interpreting effect size (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

Table 18. Variables in the Equation for Hypothesis 2

							95% C.I. for O.R.	
Variable	*B*	*S.E.*	*Wald*	*df*	*p value*	*O.R.*	*Lower*	*Upper*
Ethnicity			10.306	4	.036			
Ethnicity (AfricanAmerican/Black	.596	.454	1.723	1	.189	1.814	.745	4.417
Ethnicity (Hispanic)	.069	.359	.037	1	.848	1.071	.530	2.165
Ethnicity (Asian/Pacific Islander)	2.504	.863	8.419	1	.004	12.235	2.254	66.414
Ethnicity (Other)	1.040	1.147	.822	1	.365	2.830	.299	26.807
Initial Major			22.256	2	< .001			
Initial Major (Declared STEM)	.147	.328	.199	1	.655	1.158	.608	2.203
Initial Major (Declared non-STEM)	-1.982	.441	20.155	1	< .001	.138	.058	.327
Math Placement--Algebra	.004	.002	4.303	1	.038	1.004	1.000	1.007
CTI DMC Change	.040	.026	2.329	1	.127	1.040	.989	1.095
Constant	-1.053	.584	3.249	1	.071	.349		

Note: O.R. = Odds Ratio

The Wald test within logistic regression helps determine the significance of the coefficient for each predictor in the model by dividing the squared coefficient for each variable by its squared standard error (Tabachnick & Fidell, 2013). Based on the results of the Wald test, Initial Major was the most statistically significant predictor ($p < .001$). The results indicated that participants from the Declared STEM group had approximately a 1.2 times higher likelihood of being in the retained outcome group (eta squared = .002); however, for participants in the Declared non-STEM category, the odds of participants in this group being in the retained outcome group decrease by a factor of .138 (eta squared = .230). Ethnicity was another predictor variable that was a significant predictor at the .05 level. As with Hypothesis 1, all of the categories had odds ratios above 1, indicating that the African American/Black, Hispanic, Asian/Pacific Islander, and Other subgroups all had higher odds of being in the retained group than the reference category of Caucasian/White students. However, the wide confidence interval range and the high odds ratio may, particularly with the Asian/Pacific Islander and Other subcategories, be the result of the small number of cases in both outcome groups for the subcategories. The Math Placement--Algebra variable was also a statistically significant predictor at the .05 level; the odds ratio for this variable indicates that for every unit increase in Math Placement--Algebra test score, the odds of being in the retained group are 1.040 times higher (eta squared < .001).

The CTI DMC Change variable was not statistically significant at the .05 level but met the Hosmer et al. (2013) recommendation for acceptable alpha levels. Because the 95 percent confidence interval range contains the value of 1.00, the researcher could not rule out the possibility that the true odds ratio is 1.00, which would indicate that this variable predicts an equal probability of a case being in either the retained or non-retained outcome. Despite not

having statistical significance at the .05 level, these variables may have contributed to the overall model and increased precision with other variables.

Examining the residual statistics for each case helped evaluate goodness of fit and identify outliers for which the model did not fit (Tabachnick & Fidell, 2013). Cook's distance measures the effect of deleting a particular case from the model; cases with high Cook's distance values should be evaluated further (Field, 2009). There were no unusually high Cook's distance values, as all were below 1.00 (Field, 2009). SPSS only identified three cases that could be considered outliers in the solution based on a standardized residual value at or above 3.00 (Field, 2009; Tabachnick & Fidell, 2013). Table 19 displays the cases that met this criterion. Upon further inspection of these individual cases, the researcher could not determine an observable trend with these outliers that may be influencing the predicted values. Eliminating these cases may have improved the model fit, but it would also have resulted in further reduction to the non-retained Asian/Pacific Islander students by one case; as this variable is already limited, the researcher kept these potential outliers in the analysis to avoid having to collapse the Ethnicity variable into fewer categories (i.e. minority/non-minority).

Table 19. Outliers in the Solution for Hypothesis 2

Case No.	Observed First Year STEM Retention	Predicted	Predicted Group	Resid	ZResid
289	Y	.078	N	.922	3.443
855	Y	.063	N	.937	3.862
860	N	.940	Y	-.940	-3.964

In summary, adding the predictors into the logistic regression model did improve the predictions made. Removing predictors with *p* values greater than .20 did increase the model fit based on the Hosmer and Lemeshow test, but slightly decreased the variance accounted for by the model, as measured by a decreased Chi-square statistic and an increased -2 Log likelihood statistic. Additionally, each R-squared value decreased by approximately two percent with the removal of more highly non-significant predictors. The Initial Major variable and the Ethnicity variable were the most significant predictors in the final model, although the Math Placement--Algebra variable and the CTI DMC change variable contributed. Overall, the model performed well in predicting retained students but only predicted non-retained students correctly with less than half of cases.

Hypothesis 3

To test the third hypothesis, which stated that 2nd year undergraduate retention in STEM majors could not be predicted by the independent variables for students in a STEM Seminar class without a career planning focus, the researcher ran a binary logistic regression with 2nd Year STEM Retention as the binary outcome variable. Categorical predictor variables included Gender (Male = 0, Female = 1), Ethnicity (Caucasian/White = 1, African American/Black = 2, Hispanic = 3, Asian/Pacific Islander = 4, Other = 5), and Initial Major (Undeclared = 1, Declared STEM = 2, Declared Non-STEM = 3). A previous researcher established the coding scheme for some of these variables, and SPSS automatically dummy coded identified categorical variables with more than two categories. Continuous variables included SAT Math scores, Math Placement--Algebra Test scores, CTI Total Change scores, CTI DMC Change Scores, CTI CA Change Scores, and CTI EC Change Scores. The sample for this analysis included 166 cases

from the STEM Seminar group after removing the univariate and multivariate outliers. The researcher used a Backward (Stepwise) Wald procedure for including variables in the model. In this procedure, the analysis initially included all predictor variables; variables with *p* values higher than a designated cutoff point were removed one by one until only variables with *p* values at or below the cutoff points remain in the model (Hosmer et al., 2013; Tabachnick & Fidell, 2013). SPSS defaults to an alpha level of .05, but Hosmer et al. (2013) recommend a more liberal cutoff point between .15 and .20. For this analysis, the researcher used a cutoff point of .20 for a predictor to be included in the model; using a higher cutoff point helped address the possibility of a stepwise approach removing a variable that still contributes to the model without having traditional statistical significance.

The logistic regression required seven steps to achieve the most parsimonious model. In the first step, which included all predictor variables, the Chi-square value was 24.667 ($df = 13$, $p < .05$) and the -2 Log likelihood statistic was 151.473. The initial model with all predictors had a Cox & Snell R Square value of .138 and a Nagelkerke R Square statistic of .211, indicating that the model with all predictors explained between 14 and 21 percent of the outcome variance. Hosmer et al. (2013) noted that R squared values for logistic regression tend to be lower than linear regression. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model fit well with the data (Chi-square = 2.680, $df = 8$, $p = .953$) because of a non-significant *p* value.

After removing six variables with *p* values greater than .20 (Gender, CTI DMC Change, Ethnicity, Math Placement--Algebra, CTI Total Change, and CTI EC Change, respectively) one by one, the Chi-square value for the model was 22.253 ($df = 4$, $p < .001$). The final model yielded a -2 Log likelihood of 153.888, a Cox & Snell R Square value of .125, and a Nagelkerke R Square value of .192. These R-Square values show that the model explains between 13 and 19

percent of the variance in the outcome. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model had a good fit (Chi-square = 2.722, *df* = 8, *p* = .951); a *p* value greater than .05 indicates support for the model (Tabachnick & Fidell, 2013).

Table 20 displays a comparison of the observed outcomes and the predicted outcomes in the final model. The final model was able to accurately predict 80.7 percent of cases, with most of the accurate predictions being in the retained group. The model predicted approximately 97 percent of the retained students accurately, but predicted the non-retained cases accurately less than one fourth of the time.

Table 20. Classification Table for Hypothesis 3

Observed 2nd Year STEM Retention	Predicted 2nd Year STEM Retention		
	No	Yes	% Correct
No	9	28	24.3
Yes	4	125	96.9
Overall Percentage			80.7

a. The cut value is .500

The final model included the following variables that met the criteria of having a *p* value at or below .20 based on the Hosmer et al (2013) recommendation: Initial Major, SAT Math, and CTI CA Change. Table 21 explains the contributions of each of these variables to the final model, including their observed significance, odds ratio, and 95 percent confidence intervals for the odds ratios. The odds ratio represents the association between an independent variable and a particular outcome (Hosmer et al., 2013). For this study, the odds ratio represents the extent to which the independent variables predict membership in the STEM retained group. Odds ratios

can be used as a measure of effect size in that odds ratios closer to 1.0 have a smaller effect (Tabachnick & Fidell, 2013); however, the researcher also converted the odds ratios to eta-squared values as another method of interpreting effect size (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

The Wald test within logistic regression helps determine the significance of the coefficient for each predictor in the model by dividing the squared coefficient for each variable by its squared standard error (Tabachnick & Fidell, 2013). Based on the results of the Wald test, Initial Major was the most statistically significant predictor ($p < .01$). The results indicated that participants from the Declared STEM group had 2.059 times higher likelihood of being in the retained outcome group (eta squared = .038); however, for participants in the Declared non-STEM category, the odds of participants in this group being in the retained outcome group decrease by a factor of .245 (eta squared = .131). The CTI CA Change variable was also a statistically significant predictor at the .05 level; the odds ratio for this variable indicates that for every unit increase in CTI CA Change score, the odds of being in the retained group are 1.117 times higher (eta squared < .001).

The SAT Math variable was not statistically significant at the .05 level but met the Hosmer et al. (2013) recommendation for acceptable alpha levels. Because the 95 percent confidence interval range contains the value of 1.00, the researcher could not rule out the possibility that the true odds ratio is 1.00, which would indicate that this variable predicts an equal probability of a case being in either the retained or non-retained outcome. Despite not having statistical significance at the .05 level, this variable may have contributed to the overall model and increased precision with other variables.

Table 21. Variables in the Equation for Hypothesis 3

							95% C.I. for O.R.	
Variable	*B*	*S.E.*	*Wald*	*df*	*p value*	*O.R.*	*Lower*	*Upper*
Initial Major			10.194	2	< .01			
Initial Major (Declared STEM)	.722	.434	2.766	1	.096	2.059	.879	4.825
Initial Major (Declared non-STEM)	-1.408	.707	3.961	1	< .05	.245	.061	.979
SAT Math	.007	.004	3.342	1	.068	1.007	1.000	1.014
CTI CA Change	.111	.051	4.697	1	.030	1.117	1.011	1.236
Constant	-3.584	2.445	2.149	1	.143	.028		

Note: O.R. = Odds Ratio

Examining the residual statistics for each case helped evaluate goodness of fit and identify outliers for which the model does not fit (Tabachnick & Fidell, 2013). There were no unusually high Cook's distance values, as all were below 1.00 (Field, 2009). SPSS only identified one case that could be considered an outlier in the solution based on a standardized residual value at or above 3.00 (Field, 2009; Tabachnick & Fidell, 2013). Table 22 displays the case that meets this criterion. Because the analysis only identified one outlier, the researcher could not discern any other criteria that may have contributed to the predicted value of this case. Eliminating this case would not jeopardize any of the smaller categories, so the researcher removed it and re-ran the analysis (Field, 2009).

Table 22. Outliers in the Solution for Hypothesis 3

Case No.	Observed First Year STEM Retention	Predicted	Predicted Group	Resid	ZResid
1410	N	.908	Y	-.908	-3.143

As with the previous run of the model, the logistic regression required seven steps to achieve the most parsimonious model. In the first step, which included all predictor variables, the Chi-square value was 26.654 (*df* = 13, $p < .05$). After removing six variables with *p* values greater than .20 (Gender, CTI EC Change, Ethnicity, Math Placement--Algebra, CTI Total Change, and CTI EC Change, respectively) one by one, the Chi-square value for the model was 24.208 (*df* = 4, $p < .001$). The final model yielded a -2 Log likelihood of 148.909, a Cox & Snell R Square value of .136, and a Nagelkerke R Square value of .210. These R-Square values showed that the model explains between 13 and 19 percent of the variance in the outcome, which was a slight improvement from the first run of this model. The Hosmer and Lemeshow

Goodness of Fit Test indicated that the model had a good fit but yielded slightly different statistics (Chi-square = 3.968, *df* = 8, *p* = .860); a *p* value greater than .05 indicates support for the model (Tabachnick & Fidell, 2013).

The final model was able to accurately predict 81.2 percent of cases, with most of the accurate predictions being in the retained group; because the removed case was in the non-retained group, the percentage of correctly predicted non-retained students increased slightly. Table 23 displays a comparison of the observed outcomes and the predicted outcomes. Despite minimal improvement from the first run of this model, the final version still only predicted the non-retained students correctly one fourth of the time.

Table 23. Classification Table for Hypothesis 3B

		Predicted Year 2 STEM Retention		
Observed Year 2 STEM Retention		No	Yes	% Correct
	No	9	27	25.0
	Yes	4	125	96.9
Overall Percentage				81.2

a. The cut value is .500

The final model included the following variables that met the criteria of having a *p* value at or below .20 based on the Hosmer et al. (2013) recommendation: Initial Major, SAT Math, and CTI CA Change. Table 24 explains the contributions of the variables that were included in the final model, including their observed significance, odds ratio, and 95 percent confidence intervals for the odds ratios. As with the first run of this model, the researcher converted the odds ratios to eta-squared values as another method of interpreting effect size (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

Table 24. Variables in the Equation for Hypothesis 3B

							95% C.I. for O.R.	
Variable	*B*	*S.E.*	*Wald*	*df*	*p value*	*O.R.*	*Lower*	*Upper*
Initial Major			10.908	2	< .01			
Initial Major (Declared STEM)	.835	.445	3.526	1	.060	2.304	.964	5.507
Initial Major (Declared non-STEM)	-1.357	.709	3.664	1	.056	.257	.064	1.033
SAT Math	.008	.004	4.504	1	.034	1.008	1.001	1.016
CTI CA Change	.112	.052	4.644	1	.031	1.119	1.010	1.239
Constant	-4.480	2.527	3.142	1	.076	.011		

Note: O.R. = Odds Ratio

Based on the results of the Wald test, Initial Major was still the most statistically significant predictor ($p < .01$). The results indicated that participants from the Declared STEM group had 2.3 times higher likelihood of being in the retained outcome group (eta squared = .050); however, for participants in the Declared non-STEM category, the odds of participants in this group being in the retained outcome group decrease by a factor of .257 (eta squared = .123). The CTI CA Change variable was also a statistically significant predictor at the .05 level; the odds ratio for this variable indicates that for every unit increase in CTI CA Change score, the odds of being in the retained group are 1.119 times higher (eta squared = .001). In this re-run of the model, the SAT Math variable was also statistically significant at the .05 level. The 95 percent confidence interval for SAT Math no longer includes the 1.000 value, but the lower bound was only 1.001; as such, the interpretation the odds ratio of 1.008 (eta squared < .001), which only represents an increase of .001, was largely similar to the first run of the model.

In summary, adding the predictors into the logistic regression model slightly decreased the percentage of accurate predictions from 81.8 percent to 81.2 percent. Removing predictors with *p* values greater than .20 did increase the model fit based on the Hosmer and Lemeshow test, but slightly decreased the variance accounted for by the model, as measured by a decreased Chi-square statistic and an increased -2 Log likelihood statistic. Additionally, each R-squared value decreased by one to two percent with the removal of more highly non-significant predictors. The Initial Major variable, the SAT Math variable, and the CTI CA Change variable were all statistically significant, with the Initial Major variable having a larger effect. Overall, the model accurately predicted nearly all of the retained students but only predicted non-retained students correctly with one fourth of cases.

Summary for Hypotheses 1 through 3

Hypothesis 1 examined the influence of predictor variables on 2nd Year STEM Retention with all cases, whereas Hypotheses 2 and 3 separately examined the influence of predictors for the Career Planning group and the STEM Seminar group, respectively. Table 25 compares the base model and final model for each of hypotheses. In all three models, removing predictors with *p* values above .20 decreased the Chi-square statistic, increased the -2 Log likelihood, and decreased the R Square values, indicating that including all predictors accounted for more variance in retention outcomes. Moreover, removing highly non-significant predictors increased the Goodness of Fit with Hypotheses 1 and 2 and decreased the number of accurate predictions with Hypotheses 2 and 3. Whereas some statistics improved by using the Backward Stepwise approach, the inclusion of all predictors appears to be the better option for making predictions.

The models for each hypothesis included a different set of predictors, indicating that the predictors operated differently between the two groups. Each model more accurately predicted the retained students (80.2 to 96.9 percent of cases) rather than the non-retained students (25.0 to 47.4 percent of cases). Initial major was the most significant predictor across all three models, with the Initial STEM declared group consistently having a higher odds ratio of being in the retained group. Ethnicity was only retained in the models that included the Career Planning students, and Gender was removed from all three models. The model from Hypothesis 1 (both groups) retained both math variables, whereas Hypothesis 2 (only Career Planning students) retained the Math Placement--Algebra test and Hypothesis 3 (only STEM Seminar students) retained the SAT Math test. The CTI Change scores retained in the models also varied across groups with the Total change score in the first model, DMC change in the second model, and CA change in the third model.

Table 25. Comparison of Results from Hypotheses 1 through 3

	Hypothesis 1		*Hypothesis 2*		*Hypothesis 3*	
	Base Model	*Final Model*	*Base Model*	*Final Model*	*Base Model*	*Final Model*
Chi-square value	92.445*	91.011*	50.227*	45.857*	26.654**	24.208*
-2 Log likelihood	452.054	453.488	291.277	295.646	146.463	148.909
Cox & Snell R Square	.201	.198	.184	.169	.149	.136
Nagelkerke R Square	.274	.270	.246	.226	.230	.210
Goodness of Fit Test	p = .586	p = .617	p = .308	p = .598	p = .535	p = .860
% Correct Predictions	72.4	73.4	70.9	64.8	81.8	81.2
Variables in the Model	All	Ethnicity, Initial Major, STEM Course Participation, SAT Math, MP-Algebra, CTI Total Change	All	Ethnicity, Initial Major, MP Algebra, CTI DMC Change	All	Initial Major, SAT Math, CTI CA Change

* = p < .001; ** = p < .05

Hypothesis 4

To test the fourth null hypothesis, which stated that 3rd year undergraduate retention in STEM majors could not be predicted by the independent variables, the researcher ran a binary logistic regression with 3rd Year STEM Retention as the binary outcome variable. Categorical predictor variables included Gender (Male = 0, Female = 1), Ethnicity (Caucasian/White = 1, African American/Black = 2, Hispanic = 3, Asian/Pacific Islander = 4, Other = 5), Initial Major (Undeclared = 1, Declared STEM = 2, Declared Non-STEM = 3), and Career Planning Participation (Career Planning = 1, STEM Seminar = 2). A previous researcher established the coding scheme for some of these variables, and SPSS automatically dummy coded identified categorical variables with more than two categories. Continuous variables included SAT Math scores, Math Placement--Algebra Test scores, CTI Total Change scores, CTI DMC Change Scores, CTI CA Change Scores, and CTI EC Change Scores. The sample for this analysis included 263 cases after removing the univariate and multivariate outliers. The researcher used a Backward (Stepwise) Wald procedure for including variables in the model. In this procedure, the analysis initially included all predictor variables; variables with *p* values higher than a designated cutoff point were removed one by one until only variables with *p* values at or below the cutoff points remained in the model (Hosmer et al., 2013; Tabachnick & Fidell, 2013). SPSS defaults to an alpha level of .05, but Hosmer et al. (2013) recommend a more liberal cutoff point between .15 and .20. For this analysis, the researcher used a cutoff point of .20 for a predictor to be included in the model; using a higher cutoff point helped address the possibility of a stepwise approach removing a variable that still contributes to the model without having traditional statistical significance.

The logistic regression required six steps to achieve the most parsimonious model. In the first step, which included all predictor variables, the Chi-square value was 58.710 (df = 14, p < .001) and the -2 Log likelihood statistic was 305.030. The initial model with all predictors had a Cox & Snell R Square value of .200 and a Nagelkerke R Square statistic of .267, indicating that the model with all the predictors explained between 20 and 27 percent of the variance in the outcome. Hosmer et al. (2013) noted that R squared values for logistic regression tend to be lower than linear regression. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model fit well with the data (Chi-square = 11.238, df = 8, p = .189) because of the non-significant p value.

After removing five variables with p values greater than .20 (CTI CA Change, CTI DMC Change, Gender, CTI EC Change, and CTI Total Change, respectively) one by one, the Chi-square value for the model was 55.835 (df = 9, p < .001). The final model yielded a -2 Log likelihood of 307.904, a Cox & Snell R Square value of .191, and a Nagelkerke R Square value of .255. These R-Square values show that the model explains between 19 and 26 percent of the variance in the outcome. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model had a good fit (Chi-square = 9.187, df = 8, p = .327); a p value greater than .05 indicates support for the model (Tabachnick & Fidell, 2013).

Table 26 displays a comparison of the observed outcomes and the predicted outcomes. The final model was able to accurately predict 70.0 percent of cases, with most of the accurate predictions being in the non-retained group. The model predicted approximately 67 percent of the retained cases and approximately 73 percent of the non-retained cases.

Table 26. Classification Table for Hypothesis 4

Observed 3rd Year STEM Retention	Predicted 3rd Year STEM Retention		
	No	Yes	% Correct
No	101	38	72.7
Yes	41	83	66.9
Overall Percentage			70.0

a. The cut value is .500

The final model included the following variables that met the criteria of having a *p* value at or below .20 based on the Hosmer et al (2013) recommendation: Ethnicity, Initial Major, Career Planning Participation, SAT Math, and Math Placement--Algebra. Table 27 explains the contributions of the variables that were included in the model, including their observed significance, odds ratio, and 95 percent confidence intervals for the odds ratios. As a reminder, the odds ratio represents the association between an independent variable and a particular outcome (Hosmer et al., 2013). For this analysis, the odds ratio represents the extent to which the independent variables predict membership in the STEM retained group. Odds ratios can be used as a measure of effect size in that odds ratios closer to 1.0 have a smaller effect (Tabachnick & Fidell, 2013); however, the researcher also converted the odds ratios to eta-squared values as another method of interpreting effect size (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

Table 27. Variables in the Equation for Hypothesis 4

							95% C.I. for O.R.	
Variable	*B*	*S.E.*	*Wald*	*df*	*p value*	*O.R.*	*Lower*	*Upper*
Ethnicity			6.445	4	.168			
Ethnicity (African American/Black	.542	.448	1.467	1	.226	1.719	.715	4.134
Ethnicity (Hispanic)	.243	.349	.484	1	.487	1.275	.643	2.528
Ethnicity (Asian/Pacific Islander)	1.636	.698	5.494	1	.019	5.137	1.307	20.185
Ethnicity (Other)	.403	.684	.347	1	.556	1.497	.391	5.725
Initial Major			17.362	2	< .001			
Initial Major (Declared STEM)	.223	.328	.460	1	.498	1.250	.656	2.379
Initial Major (Declared non-STEM)	-1.792	.468	14.664	1	< .001	.167	.067	.417
STEM Seminar (Non-CP)	.588	.323	3.327	1	.068	1.801	.957	3.389
SAT Math	.004	.003	2.536	1	.111	1.004	.999	1.010
Math Placement--Algebra	.005	.002	5.449	1	.020	1.005	1.001	1.009
Constant	-2.994	1.378	4.717	1	.030	.050		

Note: O.R. = Odds Ratio

The Wald test within logistic regression helps determine the significance of the coefficient for each predictor in the model by dividing the squared coefficient for each variable by its squared standard error (Tabachnick & Fidell, 2013). Based on the results of the Wald test, Initial Major was the most statistically significant predictor ($p < .001$). The results indicated that participants from the Declared STEM group had a 1.25 times higher likelihood of being in the retained outcome group (eta squared = .004); however, for participants in the Declared non-STEM category, the odds of participants in this group being in the retained outcome group decrease by a factor of .167 (eta squared = .196). The Math Placement--Algebra variable was also statistically significant at the .05 level; the odds ratio for this variable indicates that for every unit increase in Math Placement--Algebra test score, the odds of being in the retained group are 1.005 times higher (eta squared < .001).

The remaining variables included in the model (Ethnicity, Career Planning Participation, and SAT Math) were not statistically significant at the .05 level but met the Hosmer et al. (2013) recommendation for acceptable alpha levels. With the Ethnicity variable, the African American/ Black, Hispanic, Asian/Pacific Islander, and Other subgroups all had higher odds ratios of being in the retained group than the White/Caucasian reference category. Similarly, the STEM Seminar group was 1.8 times more likely to be in the retained group than the Career Planning group. However, because the 95 percent confidence interval range contains the value of 1.00, the researcher could not rule out the possibility that the true odds ratio is 1.00, which would indicate that this variable predicts an equal probability of a case being in either the retained or non-retained outcome. Despite not having statistical significance at the .05 level, these variables may have contributed to the overall model and increased precision with other variables.

Examining the residual statistics for each case helped evaluate goodness of fit and identify outliers for which the model did not fit (Tabachnick & Fidell, 2013). There were no unusually high Cook's distance values, as all were below 1.00 (Field, 2009). SPSS only identified one case that was considered an outlier in the solution based on a standardized residual value at or above 3.00 (Field, 2009; Tabachnick & Fidell, 2013). Table 28 displays the case that met this criterion. Because the analysis only identified one outlier, the researcher could not discern any other criteria that may have contributed to the predicted value of this case. Eliminating this case did not jeopardize any of the smaller categories, so the researcher removed it and re-ran the analysis (Field, 2009).

Table 28. Outliers in the Solution for Hypothesis 4

Case No.	Observed First Year STEM Retention	Predicted	Predicted Group	Resid	ZResid
289	Y	.046	N	.954	4.543

After removing the one outlier and re-running the model, the logistic regression required six steps to achieve the most parsimonious model. In the first step, which included all predictor variables, the Chi-square value was 63.263 (df = 14, p < .001) and the -2 Log likelihood statistic was 298.969. After removing four variables with p values greater than .20 (CTI CA Change, CTI DMC Change, Gender, CTI EC Change, and CTI Total Change, respectively) one by one, the Chi-square value for the model was 60.805 (df = 9, p < .001). The final model yielded a -2 Log likelihood of 301.427, a Cox & Snell R Square value of .207, and a Nagelkerke R Square value of .277. These R-Square values showed that the model explained between 21 and 28 percent of the variance in the outcome. The Hosmer and Lemeshow Goodness of Fit Test

indicated that the model had a good fit (Chi-square = 10.975, *df* = 8, *p* = .203); a *p* value greater than .05 indicates support for the model (Tabachnick & Fidell, 2013). This *p* value was the lowest significance level for any of the models tested thus far. However, the final model was able to accurately predict 71.0 percent of cases, with most of the accurate predictions being in the non-retained group. Table 29 displays a comparison of the observed outcomes and the predicted outcomes. The model predicted approximately 68 percent of the retained students accurately, and predicted approximately 73 percent of the non-retained students accurately.

Table 29. Classification Table for Hypothesis 4B

		Predicted Year 2 STEM Retention		
Observed Year 2 STEM Retention		No	Yes	% Correct
	No	102	37	73.4
	Yes	39	84	68.3
Overall Percentage				71.0

a. The cut value is .500

The final model included the following variables that met the criteria of having a *p* value at or below .20 based on the Hosmer et al (2013) recommendation: Ethnicity, Initial Major, Career Planning Participation, SAT Math, and Math Placement--Algebra. Table 30 explains the contributions of the variables that were included in the model, including their observed significance, odds ratio, and 95 percent confidence intervals for the odds ratios. For this analysis, the odds ratio represented the extent to which the independent variables predict membership in the STEM retained group. As with previous analyses, the researcher converted the odds ratios to eta-squared values as another method of interpreting effect size (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

Table 30. Variables in the Equation for Hypothesis 4B

							95% C.I. for O.R.	
Variable	*B*	*S.E.*	*Wald*	*df*	*p value*	*O.R.*	*Lower*	*Upper*
Ethnicity			7.942	4	.131			
Ethnicity (African American/ Black	.596	.453	1.730	1	.188	1.815	.747	4.411
Ethnicity (Hispanic)	.290	.354	.675	1	.411	1.337	.669	2.673
Ethnicity (Asian/Pacific Islander)	1.757	.721	5.940	1	.015	5.794	1.411	23.798
Ethnicity (Other)	.407	.687	.351	1	.553	1.503	.391	5.779
Initial Major			18.643	2	< .001			
Initial Major (Declared STEM)	.211	.331	.406	1	.524	1.235	.646	2.360
Initial Major (Declared non-STEM)	-1.996	.497	16.104	1	< .001	.136	.051	.360
STEM Seminar (Non-CP)	.601	.326	3.403	1	.065	1.824	.963	3.455
SAT Math	.004	.003	2.137	1	.144	1.004	.999	1.010
Math Placement--Algebra	.005	.002	6.971	1	.008	1.005	1.001	1.009
Constant	-4.543	1.652	7.564	1	.006	.011		

Note: O.R. = Odds Ratio

The Wald test within logistic regression helps determine the significance of the coefficient for each predictor in the model by dividing the squared coefficient for each variable by its squared standard error (Tabachnick & Fidell, 2013). Based on the results of the Wald test, Initial Major was still the most statistically significant predictor ($p < .001$). The results indicated that participants whose initial major category Declared STEM group had a 1.2 times higher likelihood of being in the retained outcome group (eta squared = .003); however, for participants in the Declared non-STEM category, the odds of participants in this group being in the retained outcome group decrease by a factor of .136 (eta squared = .232). The Math Placement--Algebra variable was also a statistically significant predictor at the .05 level; the odds ratio for this variable indicates that for every unit increase in Math Placement--Algebra test score, the odds of being in the retained group were 1.005 times higher (eta squared < .001). In this re-run of the model, the Ethnicity, Career Planning Participation, and SAT Math variables were still not significant at the .05 level but met the Hosmer et al. (2013) recommendation for acceptable alpha levels.

In summary, adding the predictors into the logistic regression model slightly increased the percentage of accurate predictions from 69.1 percent to 71.0 percent. Removing predictors with *p* values greater than .20 slightly decreased the model fit based on the Hosmer and Lemeshow test and slightly decreased the variance accounted for by the model, as measured by a decreased Chi-square statistic and an increased -2 Log likelihood statistic. Additionally, each R-squared value decreased by approximately one percent with the removal of more highly non-significant predictors. The Initial Major variable and the Math Placement--Algebra test were statistically significant predictors, with the Initial Major variable having a larger effect. The Ethnicity variable, the STEM Course Participation variable, and the SAT Math variable were not

statistically significant at the .05 level but still contributed to the model. Unlike Hypotheses 1 through 3, the model in Hypothesis 4 more accurately predicted the non-retained students (73.4 percent) than the retained students (68.3 percent) with an overall accuracy with 71 percent of cases.

Hypothesis 5

To test the fifth hypothesis, which stated that 3rd year undergraduate retention in STEM majors could not be predicted by the independent variables for students in a STEM-focused career planning class, the researcher ran a binary logistic regression with 3rd Year STEM Retention as the binary outcome variable. Categorical predictor variables included Gender (Male = 0, Female = 1), Ethnicity (Caucasian/White = 1, African American/Black = 2, Hispanic = 3, Asian/Pacific Islander = 4, Other = 5), and Initial Major (Undeclared = 1, Declared STEM = 2, Declared Non-STEM = 3). A previous researcher established the coding scheme for some of these variables, and SPSS automatically dummy coded identified categorical variables with more than two categories. Continuous variables included SAT Math scores, Math Placement--Algebra Test scores, CTI Total Change scores, CTI DMC Change Scores, CTI CA Change Scores, and CTI EC Change Scores. The sample for this analysis included 179 cases from the Career Planning group after removing the univariate and multivariate outliers. The researcher used a Backward (Stepwise) Wald procedure for including variables in the model. In this procedure, the analysis initially included all predictor variables; variables with *p* values higher than a designated cutoff point were removed one by one until only variables with *p* values at or below the cutoff points remained in the model (Hosmer et al., 2013; Tabachnick & Fidell, 2013). SPSS defaults to an alpha level of .05, but Hosmer et al. (2013) recommend a more liberal cutoff point

between .15 and .20. For this analysis, the researcher used a cutoff point of .20 for a predictor to be included in the model; using a higher cutoff point helped address the possibility of a stepwise approach removing a variable that still contributes to the model without having traditional statistical significance.

The logistic regression required four steps to achieve the most parsimonious model. In the first step, which included all predictor variables, the Chi-square value was 40.546 (df = 13, p < .001) and the -2 Log likelihood statistic was 199.897. The initial model with all predictors had a Cox & Snell R Square value of .203 and a Nagelkerke R Square value of .274, indicating that the model with all the predictors explained between 20 and 27 percent of the variance in the outcome. Hosmer et al. (2013) noted that R squared values for logistic regression tend to be lower than linear regression. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model fit well with the data (Chi-square = 7.007, df = 8, p = .536) because of a non-significant p value.

After removing three variables with p values greater than .20 (CTI DMC Change, Math Placement--Algebra, and CTI CA Change, respectively) one by one, the Chi-square value for the model was 37.485 (df = 10, p < .001). The final model yielded a -2 Log likelihood of 202.958, a Cox & Snell R Square value of .189, and a Nagelkerke R Square value of .256. These R-Square values showed that the model explained between 19 and 26 percent of the variance in the outcome. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model had a good fit (Chi-square = 9.659, df = 8, p = .290); a p value greater than .05 indicated support for the model (Tabachnick & Fidell, 2013).

The final model was able to accurately predict 67.6 percent of cases, with most of the accurate predictions being in the non-retained group. Table 31 displays a comparison of the

observed outcomes and the predicted outcomes. The model predicted approximately 80 percent of the non-retained students accurately, but only predicted the retained students correctly approximately half the time.

Table 31. Classification Table for Hypothesis 5

	Predicted 3rd Year STEM Retention		
Observed 3rd Year STEM Retention	No	Yes	% Correct
No	86	22	79.6
Yes	36	35	49.3
Overall Percentage			67.6

a. The cut value is .500

The final model included the following variables that met the criteria of having a *p* value at or below .20 based on the Hosmer et al (2013) recommendation: Gender, Ethnicity, Initial Major, SAT Math, CTI Total Change and CTI EC Change variables. Table 32 explains the contributions of the variables that were included in the model, including their observed significance, odds ratio, and 95 percent confidence intervals for the odds ratios. Once again, the odds ratio represents the association between an independent variable and a particular outcome (Hosmer et al., 2013). As with previous analyses, the researcher also converted the odds ratios to eta-squared values as another method of interpreting effect size (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

Table 32. Variables in the Equation for Hypothesis 5

							95% C.I. for O.R.	
Variable	*B*	*S.E.*	*Wald*	*df*	*p value*	*O.R.*	*Lower*	*Upper*
Gender	-.550	.363	2.293	1	.130	.577	.283	1.176
Ethnicity			8.863	4	.065			
Ethnicity (African American /Black	.951	.550	2.988	1	.084	2.587	.881	7.603
Ethnicity (Hispanic)	-.075	.447	.028	1	.867	.928	.286	2.229
Ethnicity (Asian/Pacific Islander)	2.011	.837	5.772	1	.016	7.467	1.448	38.502
Ethnicity (Other)	.973	.965	1.015	1	.314	2.645	.399	17.535
Initial Major			15.092	2	.001			
Initial Major (Declared STEM)	.124	.430	.083	1	.773	1.132	.488	2.628
Initial Major (Declared non-STEM)	-2.081	.555	14.060	1	< .001	.125	.042	.370
SAT Math	.007	.003	4.851	1	.028	1.007	1.001	1.014
CTI Total Change	.022	.012	3.405	1	.065	1.023	.999	1.047
CTI EC Change	-.105	.075	1.947	1	.163	.901	.778	1.043
Constant	-4.709	2.124	4.917	1	.027	.009		

Note: O.R. = Odds Ratio

The Wald test within logistic regression helps determine the significance of the coefficient for each predictor in the model by dividing the squared coefficient for each variable by its squared standard error (Tabachnick & Fidell, 2013). Based on the results of the Wald test, Initial Major was the most statistically significant predictor ($p = .001$). The results indicated that participants whose initial major category Declared STEM group had a 1.13 times higher likelihood of being in the retained outcome group (eta squared = .001); however, for participants in the Declared non-STEM category, the odds of participants in this group being in the retained outcome group decrease by a factor of .125 (eta squared = .247). The SAT Math variable was also statistically significant at the .05 level; the odds ratio for this variable indicates that for every unit increase in SAT Math score, the odds of being in the retained group were 1.007 times higher (eta squared < .001).

The remaining variables included in the model (Gender, Ethnicity, CTI Total Change, and CTI EC Change) were not statistically significant at the .05 level but met the Hosmer et al. (2013) recommendation for acceptable alpha levels. This model is the first within the study to retain Gender, and indicated that Female students had lower odds ($OR = .577$) of being in the retained group. As with prior models in the study, the African American/ Black, Asian/ Pacific Islander, and Other subgroups had higher odds of being in the retained group; however, Hispanic students had lower odds in this model, unlike previous models in the study. With the CTI change scores, larger decreases in CTI Total score predicted higher odds of being in the retained group, whereas larger decreases in the CTI EC score predicted lower odds of being in the retained group. Because the 95 percent confidence interval range contains the value of 1.00, the researcher could not rule out the possibility that the true odds ratio is 1.00, which would indicate that these variables predict an equal probability of a case being in either the retained or non-

retained outcome. Despite not having statistical significance at the .05 level, these variables may have contributed to the overall model and increased precision with other variables.

Examining the residual statistics for each case helps evaluate goodness of fit and identify outliers for which the model does not fit (Tabachnick & Fidell, 2013). There were no unusually high Cook's distance values, as all were below 1.00 (Field, 2009). SPSS identified no cases that could be considered an outlier in the solution based on a standardized residual value at or above 3.00 (Field, 2009; Tabachnick & Fidell, 2013).

In summary, adding the predictors into the logistic regression model slightly decreased the percentage of accurate predictions from 68.2 percent to 67.6 percent. Removing predictors with *p* values greater than .20 slightly decreased the model fit based on the Hosmer and Lemeshow test and slightly decreased the variance accounted for by the model, as measured by a decreased Chi-square statistic and an increased -2 Log likelihood statistic. Additionally, each R-squared value decreased by between one and two percent with the removal of more highly non-significant predictors. The Initial Major variable and the SAT Math test variable were statistically significant predictors, with the Initial Major variable having a larger effect. The Ethnicity variable, the Gender variable, the CTI Total Change variable, and the CTI EC Change variable were not statistically significant at the .05 level but still contributed to the model. As with Hypothesis 4, the model in Hypothesis 5 more accurately predicted the non-retained students (79.6 percent) than the retained students (49.3 percent) with an overall accuracy with 67.6 percent of cases.

Hypothesis 6

To test the sixth hypothesis, which stated that 3rd year undergraduate retention in STEM majors could not be predicted by the independent variables for students in a STEM Seminar class without a career planning focus, the researcher ran a binary logistic regression with 3rd Year STEM Retention as the binary outcome variable. Categorical predictor variables included Gender (Male = 0, Female = 1), Ethnicity (Caucasian/White = 1, African American/Black = 2, Hispanic = 3, Asian/Pacific Islander = 4, Other = 5), and Initial Major (Undeclared = 1, Declared STEM = 2, Declared Non-STEM = 3). A previous researcher established the coding scheme for some of these variables, and SPSS automatically dummy coded identified categorical variables with more than two categories. Continuous variables included SAT Math scores, Math Placement--Algebra Test scores, CTI Total Change scores, CTI DMC Change Scores, CTI CA Change Scores, and CTI EC Change Scores. The sample for this analysis included 84 cases from the STEM Seminar group after removing the univariate and multivariate outliers. This sample is below the recommended sample size of 97 provided by the power analysis, which indicates that sample size is a limitation of this analysis. The researcher used a Backward (Stepwise) Wald procedure for including variables in the model. In this procedure, the analysis initially included all predictor variables; variables with *p* values higher than a designated cutoff point were removed one by one until only variables with *p* values at or below the cutoff points remained in the model (Hosmer et al., 2013; Tabachnick & Fidell, 2013). SPSS defaults to an alpha level of .05, but Hosmer et al. (2013) recommend a more liberal cutoff point between .15 and .20. For this analysis, the researcher used a cutoff point of .20 for a predictor to be included in the model; using a higher cutoff point helped address the possibility of a stepwise approach removing a variable that still contributes to the model without having traditional statistical significance.

The logistic regression required six steps to achieve the most parsimonious model. In the first step, which included all predictor variables, the Chi-square value was 22.770 ($df = 13$, $p < .05$) and the -2 Log likelihood statistic was 87.849. The initial model with all predictors had a Cox & Snell R Square value of .237 and a Nagelkerke R Square value of .324, indicating that the model with all predictors explained between 24 and 32 percent of the variance in the outcome. Hosmer et al. (2013) noted that R squared values for logistic regression tend to be lower than linear regression. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model fit well with the data (Chi-square = 7.950, $df = 8$, $p = 438$) because of a non-significant *p* value.

After removing five variables with *p* values greater than .20 (Gender, CTI DMC Change, Ethnicity, CTI EC Change, and SAT Math, respectively) one by one, the Chi-square value for the model was 17.960 ($df = 5$, $p < .01$). The final model yielded a -2 Log likelihood of 92.659, a Cox & Snell R Square value of .192, and a Nagelkerke R Square value of .263. These R-Square values showed that the model explained between 19 and 26 percent of the variance in the outcome. The Hosmer and Lemeshow Goodness of Fit Test indicated that the model had a good fit (Chi-square = 12.778, $df = 8$, $p = .120$); a *p* value greater than .05 indicates support for the model (Tabachnick & Fidell, 2013). This analysis had the lowest significance level for the Hosmer and Lemeshow test; however, it also had the smallest sample. However, the final model was able to accurately predict 71.4 percent of cases, with most of the accurate predictions being in the retained group. Table 33 displays a comparison of the observed outcomes and the predicted outcomes. The model predicted approximately 85 percent of the retained students accurately, but predicted the non-retained students accurately with less than half of the cases.

Table 33. Classification Table for Hypothesis 6

Observed 3rd Year STEM Retention	Predicted 3rd Year STEM Retention		
	No	Yes	% Correct
No	15	16	48.4
Yes	8	45	84.9
Overall Percentage			71.4

a. The cut value is .500

The final model included the following variables that met the criteria of having a *p* value at or below .20 based on the Hosmer et al (2013) recommendation: Initial Major, Math Placement--Algebra, CTI Total Change, and CTI CA Change. Table 34 explains the contributions of the variables that were included in the model, including their observed significance, odds ratio, and 95 percent confidence intervals for the odds ratios. As with previous analyses, the odds ratio represents the extent to which the independent variables predict membership in the STEM retained group. Additionally, the researcher converted the odds ratios to eta-squared values as another method of interpreting effect size (Borenstein, Hedges, Higgins, & Rothstein, 2009; Cohen, 1988).

Table 34. Variables in the Equation for Hypothesis 6

							95% C.I. for O.R.	
Variable	*B*	*S.E.*	*Wald*	*df*	*p value*	*O.R.*	*Lower*	*Upper*
Initial Major			4.549	2	.103			
Initial Major (Declared STEM)	.850	.569	2.230	1	.135	2.340	.767	7.142
Initial Major (Declared non-STEM)	-.911	.991	.845	1	.358	.402	.058	2.805
Math Placement--Algebra	.010	.004	8.179	1	.004	1.010	1.003	1.018
CTI Total Change	-.038	.026	2.084	1	.149	.963	.914	1.014
CTI CA Change	.199	.094	4.486	1	.034	1.220	1.015	1.466
Constant	-3.182	1.293	6.054	1	.014	.041		

Note: O.R. = Odds Ratio

Based on the results of the Wald test, Math Placement--Algebra was the most statistically significant predictor ($p < .01$); the odds ratio for this variable indicates that for every unit increase in Math Placement--Algebra score, the odds of being in the retained group were 1.01 times higher (eta squared < .001). The CTI CA Change variable was also a statistically significant predictor at the .05 level; the odds ratio for this variable indicates that for every unit increase in CTI CA Change, the odds of being in the retained group increase were 1.2 times higher (eta squared = .003).

The Initial Major and CTI Total Change variables were not statistically significant at the .05 level but met the Hosmer et al. (2013) recommendation for acceptable alpha levels. As with previous models in this study, the Initial STEM Declared group had higher odds (*OR* = 2.340) of being in the retained group, and the Initial non-STEM Declared group had lower odds (*OR* = .402) of being in the retained group. Larger decreases in the CTI Total score predicted lower odds of being in the retained group. Because the 95 percent confidence interval range contains the value of 1.00, the researcher could not rule out the possibility that the true odds ratio is 1.00, which would indicate that this variable predicts an equal probability of a case being in either the retained or non-retained outcome. Despite not having statistical significance at the .05 level, these variable may have contributed to the overall model and increased precision with other variables.

Examining the residual statistics for each case helps evaluate goodness of fit and identify outliers for which the model does not fit (Tabachnick & Fidell, 2013). There were no unusually high Cook's distance values, as all were below 1.00 (Field, 2009). SPSS identified no cases that could be considered an outlier in the solution based on a standardized residual value at or above 3.00 (Field, 2009; Tabachnick & Fidell, 2013).

In summary, adding the predictors into the logistic regression model decreased the percentage of accurate predictions from 75.0 percent to 71.4 percent. Removing predictors with *p* values greater than .20 slightly decreased the model fit based on the Hosmer and Lemeshow test and decreased the variance accounted for by the model, as measured by a decreased Chi-square statistic and an increased -2 Log likelihood statistic. Additionally, each R-squared value decreased with the removal of more highly non-significant predictors. The Math Placement--Algebra variable and the CTI CA Change variable were statistically significant predictors, with the CTI CA Change variable having a larger effect. The Initial Major variable and the CTI Total Change variable were not statistically significant at the .05 level but still contributed to the model. Unlike with Hypotheses 4 and 5, the model in Hypothesis 6 more accurately predicted the retained students (84.9 percent) than the non-retained students (48.4 percent) with an overall accuracy with 71.4 percent of cases. Due to the lower sample size and the small number of cases for some predictor variables, the researcher encourages readers to examine these results with caution.

Summary for Hypotheses 4 through 6

Hypothesis 4 examined the influence of predictor variables on 3rd Year STEM Retention with all cases, whereas Hypotheses 5 and 6 separately examined the influence of predictors for the Career Planning group and the STEM Seminar group, respectively. Table 35 compares the base model and final model for each of hypotheses. In all three models, removing predictors with *p* values above .20 decreased the Chi-square statistic, increased the -2 Log likelihood, and decreased the R Square values, indicating that including all predictors accounted for more variance in retention outcomes. Moreover, removing highly non-significant predictors decreased

the Goodness of Fit with Hypotheses 4 through 6 and decreased the number of accurate predictions with Hypotheses 5 and 6. Whereas some statistics improved by using the Backward Stepwise approach, the inclusion of all predictors appears to be the better option for making predictions.

The models for each hypothesis included a different set of predictors, indicating that the predictors operated differently between the two groups. The models in Hypotheses 4 and 5 that both included the Career Planning students more accurately predicted the non-retained students (73.4 to 79.6 percent of cases) rather than the retained students (49.3 to 68.3 percent of cases); the model in Hypothesis 6 including only the STEM Seminar students more accurately predicted the retained students (84.9 percent of cases) than the non-retained students (48.4 percent of cases). Initial major was retained in all three models, with the Initial STEM declared group consistently having a higher odds ratio of being in the retained group. Ethnicity was only retained in the models that included the Career Planning students, and Gender was retained in the model that only examined Career Planning students. The model from Hypothesis 4 (both groups) retained both math variables, whereas Hypothesis 5 (only Career Planning students) retained the SAT Math test and Hypothesis 6 (only STEM Seminar students) retained the Math Placement--Algebra test. CTI Change scores were only retained in the models examining the two groups individually and varied in their degree of influence.

Table 35. Comparison of Results from Hypotheses 4 through 6

	Hypothesis 1		*Hypothesis 2*		*Hypothesis 3*	
	Base Model	*Final Model*	*Base Model*	*Final Model*	*Base Model*	*Final Model*
Chi-square value	63.263*	60.805*	40.546*	37.485*	22.770***	17.960**
-2 Log likelihood	298.969	301.427	199.897	202.958	87.849	92.659
Cox & Snell R Square	.215	.207	.203	.189	.237	.192
Nagelkerke R Square	.286	.277	.274	.256	.324	.263
Goodness of Fit Test	$p = .270$	$p = .203$	$p = .536$	$p = .290$	$p = .438$	$p = .120$
% Correct Predictions	69.1	71.0	68.2	67.6	75.0	71.4
Variables in the Model	All	Ethnicity, Initial Major, STEM Course Participation, SAT Math, MP-Algebra	All	Gender, Ethnicity, Initial Major, SAT Math, CTI Total Change, CTI EC Change	All	Initial Major, MP Algebra, CTI Total Change, CTI CA Change

* = $p < .001$; ** = $p < .01$; *** = $p < .05$

Overall Summary

Predictive findings varied across each logistic regression model; however, the base model consistently had better Chi-square values, -2 Log likelihood statistics, and R square values than the model only including predictors with *p* values greater than .20. The percentage of accurate predictions and the Goodness of Fit statistics inconsistently changed with the removal of highly non-significant predictors. All six models retained the Initial major variable and indicated that Initially STEM Declared students had higher odds of being in the retained group and Initially non-STEM Declared students had lower odds of being in the retained group. The Ethnicity variable was retained only in the models that included Career Planning students (Hypotheses 1, 2, 4, and 5) and indicated that students in the ethnic minority subgroups had higher odds of being in the retained group, except for the Hispanic subgroup in Hypothesis 5. Gender was retained only in Hypothesis 5, denoting that the female students had lower odds of being in the retained group in their third year of college. Both math variables were retained in models containing both groups, whereas models examining the groups individually retained either the SAT Math variable or the Math Placement--Algebra variable. The CTI Change variables performed inconsistently. However, greater decreases in CTI Change scores predicted increased odds of being in the retained group, except with EC Change in Hypothesis 5 and Total Change in Hypothesis 6. Overall, the models varied in their correct predictions of retention outcomes, but each model showed a moderately strong to strong ability to predict at least one of the retention outcomes.

CHAPTER V: DISCUSSION

Introduction

The purpose of this study was to use quantitative research methods to determine the degree to which demographic variables, math ability, and career related factors could predict STEM major retention or attrition in undergraduates participating in a STEM recruitment and retention program. As previous research on retention in STEM majors has largely overlooked career-related variables as predictors, the researcher was particularly interested in investigating such variables to begin to fill a critical gap in the literature. In this discussion section, the researcher reviews key concepts and elements of the study's design and analysis procedures, explains the results of the study within the context of theory and prior research, and will describe the study's limitations, and provides implications for research and practice based on these findings.

Theoretical Constructs of the Study

Regarding demographic variables, the researcher examined existing literature related to gender and ethnicity. Females and ethnic minorities are largely underrepresented overall in STEM fields (NAS, 2011; NCSES, 2015; NMSI, 2016, NSF, 2013). Researchers have attributed these disparities to stereotype threat (i.e. group-based performance anxiety; Beasley & Fischer, 2012; Cundiff et al., 2013), lack of mentorship (Kirschmann, 2014), and math- and science-specific issues (Cundiff et al., 2013; Litzler et al., 2014; Riegle-Crumb et al., 2012). Within this study, the researcher included gender and ethnicity as predictors for retention outcomes with both undecided and STEM-declared undergraduates.

Connections between math ability and STEM retention have long been established within the literature (Chen, 2013; Gayles & Ampaw, 2014; Litzler et al., 2014; Mattem & Patterson, 2013; Nosek & Smyth, 2011). Most commonly, researchers have utilized SAT scores in models predicting successful outcomes in STEM majors, such as relationships established between higher SAT Mathematics scores and college grade point averages. Results from other studies have shown that taking higher level math courses in high school and requiring less math remediation are associated with more positive outcomes for students majoring in STEM (Chen, 2013; Gayles & Ampaw, 2014). Moreover, interactions exist between demographic variables (e.g. race, ethnicity) and both observed and perceived math ability (Gayles & Ampaw, 2014; Litzler et al., 2014; Mattem & Patterson, 2013; Nosek & Smyth, 2011). In this study, the researcher included both the SAT Mathematics subtest score and the UCF Math Placement--Algebra subtest as predictors for retention outcomes with STEM-interested and STEM-declared undergraduates.

The theoretical framework of this study borrowed from four career development theories: (a) the Theory of Circumscription, Compromise, and Self Creation (Gottfredson, 1981); (b) the Theory of Vocational Choice (Holland, 1973); (c) Social Cognitive Career Theory (Brown & Lent, 1996); (d) Cognitive Information Processing (Peterson et al., 1991). Each theory helped explain a process or phenomenon that related to retention outcomes in STEM. The work of Gottfredson (1981) and Brown and Lent (1996) provided context to how demographic representation, stereotypes, and self-efficacy can contribute to internal developmental processes that may contribute to one's choice to not pursue or to leave a STEM major. Brown and Lent (1996) and Holland (1973) also shed light on the importance of understanding one's interests as they pertain to career. Finally, the work of Peterson et al. (1991) contextualized the impact of

career readiness and negative career thinking as they relate to retention outcomes in STEM majors. Within this study, the researcher included predictor variables related to initial major selection, participation in STEM career coursework, and change scores on a measure of career readiness. Exploring these career related variables within the context of STEM could serve to open a new world of research for professionals in counseling, higher education, and counselor education.

Preliminary Retention and Demographic Results

Regarding retention data, the researcher determined from this study that students from both tracks of the COMPASS Program have better STEM retention outcomes than other studies reported in the literature. Approximately 79 percent of students from initially undecided groups who took the STEM-focused Career Planning course are retained in a STEM major from their first year to their second year, and approximately 62 percent of these same students are retained in a STEM major from their first year to their third year. Approximately 82 percent of students who start college in a STEM major and who takes the STEM Seminar course are retained in a STEM major from their first year to their second year, and approximately 68 percent of these same students are retained in a STEM major from their first year to their third year. These percentages for both groups are higher than the approximately 52 percent STEM retention rate reported by Chen (2013) with a nationwide sample and much higher than Koenig et al.'s (2012) 30 percent at another single institution. However, it must be noted that the retention numbers for the COMPASS program represent only the first two years of college, whereas Chen (2013) and Koenig et al. (2012) represent the four to six-year retention rates; because most of the

participants had not yet reached that marker at the time of this dissertation, the researcher could not provide that number.

This sample also differed from what is commonly seen in the literature with regard to gender. Approximately 46 percent of the total sample was female, which is much higher than NMSI's (2016) report that women account for approximately 23 percent of workers in STEM fields. The researcher attributes this to the COMPASS Program's active recruitment of female students with print and web advertising that promotes female representation in STEM. Additionally, as noted in Chapter Three, the COMPASS Program's Principal Investigator and Project Director are both female administrators on campus, and program staff members intentionally recruit guest speakers and mentors that represent a diverse intersection of gender and ethnic identities. Regarding retention in a STEM major to students' 2nd year of college, females accounted for a larger percentage of the non-retained group (53.5 percent) than males (46.5 percent) and accounted for a smaller percentage of the retained group (41.1 percent) than males (58.9 percent). The numbers were similar for retention in a STEM major to students' 3rd year of college; females accounted for a larger percentage of the non-retained group (55.2 percent) than males (44.8 percent) and accounted for a smaller percentage of the retained group (44.2 percent) than males (55.8 percent). It is worth noting that the gap between female students and male students widened slightly with the progression of one year. Whereas previous literature showed wider gaps between male and female students, the data from this study are consistent with previous literature in that female students are less likely to be retained in a STEM major than their male counterparts (Cundiff et al., 2013; Gayles & Ampaw, 2014).

The participants in this study were highly consistent with previous literature based on ethnicity, as the sample was majority White students (57.6 percent; NCSES, 2015; NSF, 2013;

Palmer et al., 2011). The sample was largely representative of the University of Central Florida overall (UCF, 2017). Regarding retention in a STEM major into the second year of college, the African American/Black and Hispanic subgroups had consistent percentages in both the retained and non-retained outcomes. White students were represented in the non-retained group at a larger rate than in the retained group, whereas students in the Asian/Pacific Islander and Other categories were represented in the retained group at a larger rate than in the non-retained group; the raw numbers for the Asian/ Pacific Islander group were consistent with previous reports that identified this subgroup as well represented or overrepresented (NCSES, 2015; NSF, 2013; Palmer et al., 2011). These overall ethnicity statistics were similar for retention in STEM majors into the third year of college.

Research Hypotheses

In this study, the researcher used binary logistic regression to determine the degree to which demographic variables (gender, ethnicity, and initial major), math ability scores (SAT Math scores and Math Placement Test scores), and career development factors (STEM Course Participation and Career Thoughts Inventory [CTI] change scores) could predict undergraduate retention in STEM majors during the first two years of college. To answer the aforementioned questions, the researcher tested the following six hypotheses:

Null Hypothesis 1: First-year to second-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test

scores, SAT Math scores, STEM Course Participation (Career Planning vs. STEM Seminar), and CTI change scores.

Null Hypothesis 2: First-year to second-year undergraduate retention in STEM majors for students participating in a STEM-focused Career Planning Course cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 3: First-year to second-year undergraduate retention in STEM majors for students participating in a STEM Seminar Course (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 4: First-year to third-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, STEM Course Participation (Career Planning vs. STEM Seminar), and CTI change scores.

Null Hypothesis 5: First-year to third-year undergraduate retention in STEM majors for students participating in a STEM-focused Career Planning Course cannot be significantly

predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Null Hypothesis 6: First-year to third-year undergraduate retention in STEM majors for students participating in a STEM Seminar Course (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores.

Discussion of Findings

The study's six hypotheses aimed to identify predictors of STEM retention, with the first three hypotheses focused on retention from the first to second year of college and the latter three hypotheses focused on retention from the first to third year of college. With all six hypotheses, both the base models and the final models yielded by the stepwise procedure fit well with the data, with mixed findings on which approach to entering predictors performed best. The final models for all six hypotheses accounted for less variance than the base models, but the final models for Hypotheses 1 and 4 (including both groups) correctly predicted more cases than the respective base models. Additionally, the models more accurately predicted retained cases for first to second year retention across groups ($H0_1$ through $H0_3$) and for first to third year retention with the STEM Seminar group ($H0_6$); however, the models more accurately predicted non-retained cases for first to third year retention when the models contained the Career Planning group ($H0_4$ and $H0_5$).

The influence of individual predictors varied across groups and across the two dependent variables. Initial Major was a consistently strong predictor with both the Career Planning and STEM Seminar groups and for both 2nd and 3rd year retention. The models for all six hypotheses indicated that the Initial STEM Declared group had higher odds of retention, whereas the Initial Non-STEM Declared group had lower odds of retention, consistent with findings from Lee et al. (2015) and Lent et al. (2016). This finding was echoed in the fact that in Hypotheses 1 and 4 examining both groups, the STEM Seminar group demonstrated higher odds of being in the retained group.

Despite low numbers of cases in Ethnicity subgroups, Ethnicity was a strong predictor of retention with models containing the Career Planning group ($H0_1$, $H0_2$, $H0_4$, and $H0_5$). In these models, the ethnic minority groups had higher odds of being retained than the Caucasian/ White group, with the exception of the Hispanic group in Hypothesis 5; these findings align with the findings of Riegle-Crumb & King (2010) but are not congruent with other studies investigating ethnicity as a predictor (Chen, 2013; Cundiff et all, 2013; Gayles & Ampaw, 2014). Unlike prior literature, the models removed Gender as a predictor based on high *p* values, except in Hypothesis 5 that examined 3rd year retention with the Career Planning students only. Specific implications for that hypothesis are provided later in that respective section, but it is worth noting that the removal of Gender as a significant predictor sets this study apart from prior research (Beasley & Fischer, 2012; Cundiff et al., 2013; Gayles & Ampaw, 2014; Riegle-Crumb et al., 2012). As with prior literature (CollegeBoard, 2012; Crisp et al., 2009; Le et al., 2014; Mattem and Patterson, 2013; Rohr, 2012), math variables influenced the models, but were inconsistent as to which math variable was retained in each model. The author discusses each model's findings in the sections below.

Hypothesis 1

The first null hypothesis based on Research Question 1 stated that first-year to second-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, career planning participation, and CTI change scores. The first model examining 2nd year STEM retention across both groups from the COMPASS program retained six variables (Ethnicity, Initial Major, STEM Course participation, SAT Math, Math Placement--Algebra, and CTI Total Change score) as predictors based on Hosmer et al.'s (2013) and Tabachnick & Fidell's (2013) recommended cutoff point for inclusion. The model removed the change scores for the three subscales from the CTI and gender as predictors. This logistic regression model fit the data well based on a non-significant Goodness of Fit test and was able to accurately predict approximately three-fourths of retention outcomes; however, the model poorly predicted non-retained outcomes with just under 50 percent of cases correctly predicted. Including demographic and math related variables into the analysis greatly improved the model fit as compared to Belser et al.'s (2017) pilot study; additionally, as compared to the Belser et al. analysis, the current model predicted non-retained students with a slightly higher accuracy but decreased slightly in the overall accuracy of predictions and with predicting the retained students.

Initial major was the most significant predictor and indicated that initially STEM declared students have a higher likelihood of being retained in a STEM major, whereas STEM-interested students with a major initially declared as non-STEM were less likely to be retained. This finding is supported by the STEM course variable, which indicated that the STEM Seminar students were more than twice as likely to be retained. Because students enroll in either the

STEM Seminar or STEM-focused Career Planning course based on their level of commitment to a STEM major, it is not surprising that the students in the STEM Seminar course (i.e. those with a declared STEM major as of the first day of classes) are retained at a higher rate. A noteworthy finding is that by including demographic and math variables and by improving the overall model fit, the current model reversed the claim by Belser et al.'s (2017) model that the Career Planning students were more likely to be retained. However, the results from both of these variables are in line with previous research that indicates that goals and intended persistence in a major were significantly associated with observed retention in STEM majors (Lee et al., 2015; Lent et al., 2016). Because this key finding reversed from the Belser et al. (2017) study to this dissertation, more research is needed to replicate findings.

The ethnicity variable overall was a significant predictor; however, issues related to sample size warrant the reader to read it with caution. The data showed that African American/ Black, Hispanic, and Other students had higher likelihoods of being retained, which was supported by each of these groups having more students in the retained group than the non-retained group. However, the ratio of cases within these racial subgroups to the overall sample may have inflated these odds ratios. These findings were inconsistent with researchers who have found that underrepresented minority students were less likely to be retained in STEM majors (Chen, 2013; Cundiff et all, 2013; Gayles & Ampaw, 2014) and consistent with those who found the opposite (Riegle-Crumb & King, 2010). The predicted odds of being retained were highest for the Asian/Pacific Islander group, which was once again consistent with the observed retention outcomes. This finding was consistent with Chen (2013) and NCSES (2015) who noted that whereas this subgroup is underrepresented in the overall population, they are overrepresented in some STEM fields. Despite potential limitations with sampling, these

findings may provide initial statistical support for intervention like COMPASS that attend to demographic representation within the structure of the program.

The gender variable was removed from the model as a highly non-significant predictor. This finding is inconsistent with a wealth of literature indicating that females are less likely to be retained in STEM majors (Beasley & Fischer, 2012; Cundiff et al., 2013; Gayles & Ampaw, 2014; Riegle-Crumb et al., 2012). However, the sample in this study did not accurately reflect gender representation in STEM, as females comprised nearly half of the sample; this ratio may have skewed the retention data by decreasing the retention gap that researchers have previously observed. Another possibility is that the COMPASS Program's attention to gender related issues in STEM may have influenced female students' persistence. However, without a control group, the researcher cannot objectively make this causal claim.

The continuous variables (SAT Math, Math Placement--Algebra, and CTI Total Change) did not greatly increase the odds of students being retained but performed in the expected direction. A positive association between math related variables and STEM retention is consistent with previous literature, although the influence was not as great within this sample (CollegeBoard, 2012; Crisp et al., 2009; Le et al., 2014; Mattem and Patterson, 2013; Rohr, 2012). Similarly, researchers previously associated changes in negative career thinking with better outcomes both specific to STEM (Belser et al., 2017) and across the board (Folsom et al., 2004; Reardon et al., 2015).

Hypothesis 2

The second null hypothesis based on Research Question 1A stated that first-year to second-year undergraduate retention in STEM majors for students participating in a STEM-

focused career planning class cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores. This model examining 2nd year STEM retention with the students from the STEM-focused Career Planning course retained four variables (Ethnicity, Initial Major, Math Placement--Algebra, and CTI DMC Change score) as predictors based on Hosmer et al.'s (2013) and Tabachnick & Fidell's (2013) recommended cutoff point for inclusion. The model removed the change scores for the CTI Total and two of its subscales, SAT Math, and gender as predictors. This logistic regression model fit the data well based on a non-significant Goodness of Fit test and was able to accurately predict approximately two-thirds of retention outcomes; compared to the model from Hypothesis 1, the model was slightly better with predicting non-retained students but decreased in the percentage of accurate predictions for the retained students.

As with the results from Hypothesis 1, initial major was the most significant predictor and indicated that initially STEM declared students have a higher likelihood of being retained in a STEM major, whereas STEM-interested students with a major initially declared as non-STEM were less likely to be retained. These results are consistent with previous research that indicates that goals and intended persistence in a major were significantly associated with observed retention in STEM majors (Lee et al., 2015; Lent et al., 2016). This analysis extends these findings to students who were initially not committed to a STEM major; as noted in Chapter 3, some students had declared a major that they thought they liked but opted to take the STEM-focused Career Planning course because their major decision was not solidified. The inclusion of the CTI Decision Making Confusion subscale (albeit, not statistically significant) makes sense as this subscale evaluates negative career thinking around narrowing career options (Sampson et

al., 1996a). The Decision Making Confusion subscale specifically measures negative thinking around difficulty with narrowing career options, which is a salient concern for students who are considered undecided.

The ethnicity variable overall was a significant predictor with this subgroup of participants, as well. However, issues related to sample size warrant the reader to read it with caution. As with the results from Hypothesis 1, the data showed that African American/ Black, Hispanic, and Other students had higher likelihoods of being retained, which was supported by each of these groups having more students in the retained group than the non-retained group. However, the ratio of cases within these racial subgroups to the overall sample may have inflated these odds ratios, especially as this analysis used a subset of the overall sample. Similar to Hypothesis 1, these findings were inconsistent with researchers who have found that underrepresented minority students were less likely to be retained in STEM majors (Chen, 2013; Cundiff et all, 2013; Gayles & Ampaw, 2014) and consistent with those who found the opposite (Riegle-Crumb & King, 2010). The Asian/Pacific Islander group once again had the highest predicted odds of being retained, which was consistent with previous literature (Chen, 2013; NCSES, 2015). As with Hypothesis 1, these findings may highlight the potential of targeted STEM career programming on mediating and potentially reversing the negative effects of demographic representation in STEM.

The gender variable was once again removed from the model as a highly non-significant predictor, which is inconsistent previous literature indicating that females are less likely to be retained in STEM majors (Beasley & Fischer, 2012; Cundiff et al., 2013; Gayles & Ampaw, 2014; Riegle-Crumb et al., 2012). However, because the sample in this study did not accurately reflect gender representation in STEM, the retention data may be slightly skewed. The

COMPASS Program's attention to gender related issues in STEM might have influenced female students' persistence by mitigating the previously observed negative effects of gender underrepresentation, but without a control group, the researcher cannot objectively make this causal claim.

The Math Placement--Algebra variable did not greatly increase the odds of students being retained but performed in the expected direction. A positive association between math related variables and STEM retention is consistent with previous literature, although the influence was not as great within this sample (Crisp et al., 2009; Le et al., 2014; Rohr, 2012). Unlike the Hypothesis 1, this model removed SAT Math scores as a significant predictor, which is inconsistent with previous literature (CollegeBoard, 2012; Mattem & Patterson, 2013); however, researchers affiliated with the SAT conducted both of these previous studies. The findings of the current study could indicate that the SAT is not as good of a predictor as observed in previous studies or that the COMPASS Program's inclusion of math tutoring and designated math courses helped level the playing field for students who tested differently on the SAT.

Hypothesis 3

The third null hypothesis based on Research Question 1B stated that first-year to second-year undergraduate retention in STEM majors for students participating in a STEM seminar class (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores. This model examining 2nd year STEM retention with the students from the STEM Seminar course retained only three variables (Initial Major, CTI CA Change score, and SAT Math) as predictors based on Hosmer et al.'s (2013) and Tabachnick & Fidell's (2013) recommended cutoff point for

inclusion. The model removed gender, ethnicity, Math Placement--Algebra, the CTI Total Change score, the CTI EC Change score, and the CTI DMC Change score as predictors. This logistic regression model fit the data well based on a non-significant Goodness of Fit test and was able to accurately predict more than three-fourths of retention outcomes; compared to the models from Hypotheses 1 and 2, the model was better with predicting retained students but had a significantly weaker ability to predict non-retained students correctly.

As with the results from Hypotheses 1 and 2, initial major was the most significant predictor and once again indicated that initially STEM declared students have a higher likelihood of being retained in a STEM major, whereas STEM-interested students with a major initially declared as non-STEM were less likely to be retained. It is important to note that these particular students were uncommitted to a STEM major at the time of applying to the University but declared a major between the time of admittance and the first day of class. Some students may have included a major on their application that they were not fully committed to at that time. These students who included a major on their application to the University, however, were more likely to be retained, regardless of whether they were actually committed to that major. Similarly, the inclusion of the CTI Commitment Anxiety subscale as a significant predictor makes sense as this subscale evaluates negative career thinking around making a final career choice from narrowed career options (Sampson et al., 1996a). This finding makes a case that decreasing commitment anxiety for these students who at least a partial commitment to a STEM major improves their likelihood of being retained.

The SAT Math variable did not greatly increase the odds of students being retained but performed in the expected direction. A positive association between math related variables and STEM retention is consistent with previous literature, although the influence was not as great

within this sample (CollegeBoard, 2012; Crisp et al., 2009; Le et al., 2014; Mattem and Patterson, 2013; Rohr, 2012). Whereas two different math variables were predictors for the Career Planning group and the STEM Seminar group, the fact that both models for Hypotheses 2 and 3 included a math-related predictor supports previous research about math as a predictor for STEM success.

The gender variable and ethnicity variable both were removed from the model as non-significant predictors, which is inconsistent previous literature examining demographics and STEM retention (Beasley & Fischer, 2012; Chen, 2013; Cundiff et al., 2013; Gayles & Ampaw, 2014; Riegle-Crumb et al., 2012; Riegle-Crumb & King, 2010). Although these findings may relate to sampling issues with both variables, the findings may also provide initial support for a hypothesis that participation in a STEM recruitment and retention program can mitigate the influence on demographic underrepresentation on STEM retention. However, without a control group, the researcher cannot make this claim.

Overall Discussion of 2nd Year Retention

Hypotheses 1 through 3 examined the influence of the predictors on the 2nd Year Retention outcome variable, with the latter two hypotheses focusing on the Career Planning and STEM Seminar groups individually. As with the Belser et al. (2017) study, each of these three models more accurately predicted retained cases than non-retained cases, even after factoring in new predictors. However, adding the new predictors increased the outcome variance explained by the model and increased the model fit. The models' lower number of accurately predicted non-retained cases may relate to internal factors (e.g., self-efficacy, stereotype threat, math anxiety) identified as predictors in prior research (Beasley & Fischer, 2012; Cundiff et al., 2013;

Litzler et al., 2014). Nevertheless, the findings indicated that early declaration of a STEM major, higher performance on math assessments, and higher reductions in negative career thinking could predict higher odds of being retained in a STEM major. The Ethnicity variable, however, demonstrated that ethnic minorities had a higher odds of retention in STEM, with a higher level of significance for the undecided Career Planning students.

Hypothesis 4

The fourth null hypothesis based on Research Question 2 stated that first-year to third-year undergraduate retention in STEM majors cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, career planning participation, and CTI change scores. This model examining 3rd year STEM retention with the students from both the STEM-focused Career Planning course and the STEM Seminar course retained five variables (Initial Major, Math Placement, STEM Course Participation, SAT Math, and Ethnicity) as predictors based on Hosmer et al.'s (2013) and Tabachnick & Fidell's (2013) recommended cutoff point for inclusion. The model removed gender and all CTI Change score variables as predictors. This logistic regression model fit the data well based on a non-significant Goodness of Fit test and was able to accurately predict 70 percent of retention outcomes; compared to the models examining 2nd year STEM retention, this first model examining 3rd year STEM retention was much better with predicting non-retained students and slightly less able to predict retained students correctly.

As with 2nd year STEM Retention, the Initial major variable was the most significant predictor of 3rd year STEM Retention and indicated that initially STEM declared students have a higher likelihood of being retained in a STEM major, whereas STEM-interested students with a

major initially declared as non-STEM were less likely to be retained. This finding is supported by the STEM course variable, which indicated that the STEM Seminar students were nearly twice as likely to be retained. Because students enroll in either the STEM Seminar or STEM-focused Career Planning course based on their level of commitment to a STEM major, it is not surprising that the students in the STEM Seminar course (i.e. those with a declared STEM major as of the first day of classes) are retained at a higher rate. However, the results from both of these variables are in line with previous research that indicates that goals and intended persistence in a major were significantly associated with observed retention in STEM majors (Lee et al., 2015; Lent et al., 2016).

The continuous math variables (SAT Math and Math Placement--Algebra) did not greatly increase the odds of students being retained but performed in the expected direction. A positive association between math related variables and STEM retention is consistent with previous literature, although the influence was not as great within this sample (CollegeBoard, 2012; Crisp et al., 2009; Le et al., 2014; Mattem and Patterson, 2013; Rohr, 2012). As with the model from Hypothesis 1 that included both the Career Planning and STEM Seminar students, both math variables remained in the model.

The ethnicity variable overall was not statistically significant at the .05 level but was retained as a predictor based on the Hosmer et al. (2013) and Tabachnick & Fidell (2013) recommendation. The odds ratios for the African American/Black, Hispanic, and Other subgroups indicated a higher likelihood of being retained, which was supported by each of these groups having more students in the retained group than the non-retained group; however, as previously noted, the ratio of cases within these racial subgroups to the overall sample may have inflated these odds ratios. Similar to the results from previous hypotheses, these findings were

inconsistent with researchers who have found that underrepresented minority students were less likely to be retained in STEM majors (Chen, 2013; Cundiff et all, 2013; Gayles & Ampaw, 2014) and consistent with those who found the opposite (Riegle-Crumb & King, 2010). The Asian/Pacific Islander group once again had the highest predicted odds of being retained, which was consistent with previous literature (Chen, 2013; NCSES, 2015).

Hypothesis 5

The fifth null hypothesis based on Research Question 2A stated that first-year to third-year undergraduate retention in STEM majors for students participating in a STEM-focused career planning class cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores. This model examining 3rd year STEM retention with the students from the STEM-focused Career Planning course retained six variables (Initial Major, SAT Math, CTI Total Change score, Ethnicity, Gender, and CTI EC Change score) as predictors based on Hosmer et al.'s (2013) and Tabachnick & Fidell's (2013) recommended cutoff point for inclusion. The model removed the change scores for the CTI DMC and CA subscales and the Math Placement--Algebra test as predictors. This logistic regression model fit the data well based on a non-significant Goodness of Fit test and was able to accurately predict more than two-thirds of retention outcomes; similar to the model from Hypothesis 1, the model more accurately predicted the retained students but predicted the non-retained students correctly with less than half of the cases.

As with the results from previous hypotheses, initial major was once again the most significant predictor and indicated that initially STEM declared students have a higher likelihood of being retained in a STEM major, whereas STEM-interested students with a major initially

declared as non-STEM were less likely to be retained. These findings support previous research that indicates that goals and intended persistence in a major were significantly associated with observed retention in STEM majors (Lee et al., 2015; Lent et al., 2016). As with the results from Hypothesis 2, this analysis extends these findings to students who were initially not committed to a STEM major; as noted in Chapter 3, some students had declared a major that they thought they liked but opted to take the STEM-focused Career Planning course because their major decision was not solidified.

Neither the CTI Total Change score nor the CTI External Conflict subscale change score were statistically significant; however, the model retained both. The results indicated that increases in CTI Total Change score (i.e. decreases from pretest to posttest) increase the odds of being retained in STEM, which is consistent with previous findings specifically related to STEM (Belser et al., 2017) and across the board (Folsom et al., 2004; Reardon et al., 2015). Interestingly, increases in the CTI External Conflict Change score (i.e. decreases from pretest to posttest) slightly decreased the odds of being retained in a STEM major. This finding is inconsistent with previous literature on the CTI (Folsom et al., 2004; Reardon et al., 2015; Sampson et al., 1996a). However, it is worth noting that this is the smallest subscale on the CTI and had the smallest mean differences from pretest to posttest for the total sample and for the Career Planning and STEM Seminar groups.

The ethnicity variable overall was retained as a predictor of 3rd year STEM retention with this subgroup of participants based on the recommendation by Hosmer et al. (2013) and Tabachnick & Fidell (2013) on inclusion of predictors. As with the results from Hypothesis 1, the data showed that students in the African American/Black and Other groups had higher likelihoods of being retained, which was supported by each of these groups having more students

in the retained group than the non-retained group; however, the ratio of cases within these racial subgroups to the overall sample may have inflated these odds ratios, especially as this analysis used a subset of the overall sample. Similar to Hypothesis 1, these findings were inconsistent with researchers who have found that underrepresented minority students were less likely to be retained in STEM majors (Chen, 2013; Cundiff et all, 2013; Gayles & Ampaw, 2014) and consistent with those who found the opposite (Riegle-Crumb & King, 2010). This Hypothesis 5 model was the first within this study to find that Hispanic students were less likely to be retained in STEM, although the decrease in odds was small. The Asian/Pacific Islander group once again had the highest predicted odds of being retained, which was consistent with previous literature (Chen, 2013; NCSES, 2015); however, as noted, the reader should examine this finding with caution, as this group had the most issues with sampling.

The SAT Math variable was a significant predictor but did not greatly increase the odds of students being retained. A positive association between math related variables and STEM retention is consistent with previous literature, as researchers have demonstrated that higher SAT Math scores relate to better STEM outcomes; however, the influence of math ability was not as great within this sample as in those previous studies (CollegeBoard, 2012; Crisp et al., 2009; Le et al., 2014; Mattem and Patterson, 2013; Rohr, 2012).

This model was the first to retain the gender variable as a predictor, albeit not statistically significant. The results indicated that female students were less likely to be retained in a STEM major, which is consistent with previous literature (Beasley & Fischer, 2012; Cundiff et al., 2013; Gayles & Ampaw, 2014; Riegle-Crumb et al., 2012). The COMPASS Program's attention to gender related issues in STEM, specifically within the first year of college, might have influenced retention outcomes. However, this model may provide support for a hypothesis that

gender related concerns come back into play for initially STEM undecided students when these students are less involved with programming that specifically seeks to address issues of gender representation. Without a control group, though, the researcher cannot objectively make this causal claim.

Hypothesis 6

The sixth and final null hypothesis based on Research Question 2B stated that first-year to third-year undergraduate retention in STEM majors for students participating in a STEM seminar class (without a career development focus) cannot be significantly predicted by ethnicity, gender, initial major, Math Placement Test scores, SAT Math scores, and CTI change scores. This model examining 3rd year STEM retention with the students from the STEM Seminar course retained only four variables (Initial Major, CTI CA Change score, and SAT Math) as predictors based on Hosmer et al.'s (2013) and Tabachnick & Fidell's (2013) recommended cutoff point for inclusion. The model removed gender, CTI DMC Change, ethnicity, CTI EC Change, and SAT Math scores as predictors. This logistic regression model fit the data well based on a non-significant Goodness of Fit test and was able to accurately predict approximately 71 percent of retention outcomes. As with models from several previous hypotheses, the model was better with predicting non-retained students but accurately predicted non-retained students with less than half of the cases. However, sample size was a limitation for this model, as the sample had fewer students than what the power analysis recommended for sample size. As such, the reader should view the findings of this specific analysis with caution.

Once again, initial major was the most significant predictor and once again indicated that initially STEM declared students have a higher likelihood of being retained in a STEM major,

whereas STEM-interested students with a major initially declared as non-STEM were less likely to be retained. As with Hypothesis 3, it is important to note that these particular students were uncommitted to a STEM major at the time of applying to the University but declared a major between the time of admittance and the first day of class. Some students may have included a major on their application that they were not fully committed to at that time. These students who included a major on their application to the University, however, were more than twice as likely to be retained, regardless of whether they were actually committed to that major. Similarly, the inclusion of the CTI Commitment Anxiety subscale as a significant predictor makes sense as this subscale evaluates negative career thinking around making a final career choice from narrowed career options (Sampson et al., 1996a). This finding makes a case that decreasing commitment anxiety for these students who at least a partial commitment to a STEM major improves their likelihood of being retained. Interestingly, increases in the CTI Total Change score (i.e. decreases from pretest to posttest) slightly decreased the odds of being retained in a STEM major. This finding is inconsistent with previous literature on the CTI (Belser et al., 2017; Folsom et al., 2004; Reardon et al., 2015; Sampson et al., 1996a).

The Math Placement--Algebra variable did not greatly increase the odds of students being retained but was a significant predictor. Similar to findings from earlier hypotheses, these finding was consistent with previous literature, although the influence was not as great within this sample (CollegeBoard, 2012; Crisp et al., 2009; Le et al., 2014; Mattem & Patterson, 2013; Rohr, 2012). Whereas two different math variables were predictors of 3rd year STEM retention for the Career Planning group and the STEM Seminar group, the fact that both models for Hypotheses 5 and 6 included a math-related predictor supports previous research about math as a predictor for STEM success.

Overall Discussion of 3rd Year Retention

Hypotheses 4 through 6 examined the influence of the predictors on the 3rd Year Retention outcome variable, with the latter two hypotheses focusing on the Career Planning and STEM Seminar groups individually. In contrast to the Belser et al. (2017) study and the previous three hypotheses, the models for Hypotheses 4 and 5 more accurately predicted the non-retained cases than the retained cases. Additionally, adding the demographic and math-related predictors increased the outcome variance explained by the model and increased the model fit. As noted previously, internal factors (e.g., self-efficacy, stereotype threat, math anxiety) identified as predictors in prior research (Beasley & Fischer, 2012; Cundiff et al., 2013; Litzler et al., 2014) may have played a larger role with 2nd year retention when COMPASS Program initiatives were in place to address issues pertaining to observable factors (i.e., gender and ethnicity). However, when some of those initiatives are removed after the first year, these observable factors may become more salient with students opting to leave STEM, as evidenced by an increased ability to accurately predict non-retained cases. Nevertheless, the findings indicated that early declaration of a STEM major, higher performance on math assessments, and higher reductions in negative career thinking could predict higher odds of being retained in a STEM major.

Summary of Findings

To fill a gap in the literature on STEM major retention, this study incorporated demographic variables, math scores, and career-related variables into a predictive model of STEM retention for students participating in a STEM recruitment and retention intervention program. The findings consistently demonstrated that deciding on or declaring a STEM major prior to starting college predicts higher odds of being retained in a STEM major through the first

and second year. It is worth noting that initially being undecided yet STEM interested did not predict reduced odds of being retained in STEM; however, having an initially declared non-STEM major did predict reduced odds of being retained in STEM. Although the use of a control group could have improved the researcher's ability to make causal claims, the findings of this study to support the notion that STEM-career interventions do influence student outcomes with regard to STEM majors, particularly with improving retention and mitigating the negative effects of demographic underrepresentation. The influence of demographic variables fluctuated with the 2nd year and 3rd year retention variables, which likely related to the program structure that provides more intervention in the first year than in the second year.

The continuous variables within the study also operated as expected, although with inconsistent levels of significance. In line with prior research, higher math assessment scores predicted higher odds of being retained in STEM. However, within this study, the math variables did not predict dramatic increases in odds as seen in prior studies; it is possible that the COMPASS Program's inclusion of math tutoring and designated sections of math courses reduced the ability to predict based on math performance. Researchers previously used the Career Thoughts Inventory to demonstrate outcomes of Career Planning courses, both generic and specific to STEM majors. In this study, reductions in negative career thinking did relate to increased odds of being retained in STEM (with a few exceptions), albeit with a small effect. Due to the high effects noted by the Initial Major and STEM Course variables, the CTI pretest may be a better predictor than the change scores.

From a methodological standpoint, the Backward Stepwise approach for entering predictors improved some aspects of the model and regressed some aspects. Specifically, eliminating the highly non-significant predictors improved the number of accurately predicted

cases with Hypotheses 1 and 4 examining both groups; in other hypotheses, the number of accurately predicted cases decreased mildly with the final models. The Stepwise approach improved model fit, as measured by the Hosmer and Lemeshow Test, with the 2nd Year Retention dependent variables but did not improve model fit with the 3rd Year Retention dependent variable. Removing highly non-significant predictors may lead to underfitting the model, but based on the inconsistency of differences between the base and final models observed in this study, researchers may not want to completely dismiss the approach and carefully consider the cutoff *p* value for including predictors. However, the comparison of the two approaches provides context both for predicting STEM retention and the using binary logistic regression.

Limitations of the Study

A number of limitations exist for the current study. In this section, the researcher will present these limitations as they relate to research design, sampling, and instrumentation.

Research Design

One major limitation to this study's design is the lack of a control group, which limited the researcher's ability to make causal inferences. Instead, the researcher used a comparison group design and acknowledged that the two groups (STEM-focused Career Planning and STEM Seminar) had key differences. Both of these comparison groups were part of the UCF COMPASS Program, which was specifically designed to increase recruitment and retention in STEM majors. As such, the researcher could hypothesize that either or both of these groups could have higher STEM retention rates than a true control group of students not receiving any

additional supports. However, the researcher's inclusion of both groups and inclusion of hypotheses examining the groups separately did allow for comparisons of how the predictors operated differently with STEM-declared and undecided students.

Threats to internal validity may have also impacted retention outcomes. With regard to maturation, some of the variance in retention outcomes may be attributed to natural processes that students experienced on their own as they matriculated through college. Testing is also a threat to internal validity, as students' scores with the CTI posttest may have been influenced with their familiarity with the CTI pretest. Additionally, because students were aware that they were part of a research study and because they knew the CTI was part of a class assignment, students may have taken these assessments in a way that would decrease their scores on the posttest.

The COMPASS Program also incorporates additional elements designed to support students that the researcher did not include within the current study. It is possible that these additional variables could have provided additional statistical relevance for the analysis. For example, all students had access to academic support and tutoring for their math and science courses; however, the program does not collect data regarding students' use of these services or their perception of these services. Additionally, students in both COMPASS courses participated in structured research lab visits and hear from guest speakers, but the two courses use different surveys for gathering information about students' experiences with these activities.

Sampling

Based on the a priori power analysis, the total sample size was sufficient for all of the analyses run within this study except the analysis for Hypothesis 6. However, a larger sample

size overall may have increased generalizability. Within the sample, female students were overrepresented in relation to their representation in the larger STEM world of work; this ratio may have skewed the data set, resulting in gender not appearing as a significant predictor of STEM retention for this data set when it actually is for the general population of STEM students. Whereas the ethnicity variable was representative of the University and reflected patterns seen in other studies, the actual number of students in some categories violated the Peduzzi et al. (1996) 10 case rule and the Field (2009) five case rule for the number of cases per predictor in each outcome. As such, increasing the sample size to secure larger number of students in these ethnic minority groups would have helped the analysis. Additionally, the researcher could consider re-running the analysis with the Ethnicity variable collapsed further (e.g., merging the Asian/ Pacific Islander group with the Other group) and comparing the results in the Coefficients tables for both approaches.

Instrumentation

Due to lack of individual student data, the researcher was unable to run reliability analyses for the SAT Math subtest and the UCF Math Placement--Algebra test. Moreover, the researcher did not have access to psychometric properties for the UCF Math Placement--Algebra test. Missing data was also an issue for both the UCF Math Placement--Algebra test and the CTI, resulting in the researcher having to impute the missing values. The researcher had the opportunity to standardize the CTI administration as much as possible but had no control over the administration of the SAT Math test or the UCF Math Placement--Algebra test. Whereas the researcher checked the dataset for errors, it is possible that data entry errors exist due to the

number of research assistants who helped enter the data. Examining the data set for unusual values or outliers helped mitigate the potential for error.

Although the study is not without limitations, it does have implications for research and practice. With regard to future research studies, researchers should seek to address limitations observed in this study to improve outcomes.

Recommendations for Future Research

This research study provided an exploratory investigation of factors that could predict STEM retention using logistic regression. Based on issues with the current models, the researcher intends to address some minor design elements with the hope of improving the models' ability to accurately predict both retained and non-retained students. For example, based on the significance of the initial major variable in multiple models, the researcher hypothesizes that the CTI pretest scores may better predict STEM outcomes than the CTI change scores because a career readiness score from the first week of college may more closely relate to students' initial major decision. Additionally, the researcher may want to explore the data using a full logistic regression model with all predictors, rather than using a stepwise approach, as evidenced by the comparison of the base and final models for each hypothesis. As the sample size grows, the researcher may be able to add interaction effects between demographic variables and math scores as recommended by previous literature. The researcher may also want to re-run the analyses with the Asian/ Pacific Islander and Other subgroups combined to increase the number of cases in the combined group; the researcher could compare the Coefficients Table for each approach and determine if the sampling impacted the findings with other sub-categories.

Follow-up analyses to this study would be to extend the exploration of these variables to later years of college with the goal of identifying how well these variables could predict STEM retention through the end of college. To further explore potential mediating or moderating effects among the predictor variables, researchers may want to structural equation modeling to analyze the data; however, these analyses would need to use a different dependent variable (e.g. the CTI posttest) that is not based solely on one binary outcome. Identifying these effects would provide more context to the variables used in the present study and how they can be built in to future investigations.

Outside of this particular study, future researchers should focus on outcome-based research involving STEM-focused career planning courses that build on prior research on effective strategies for STEM. Prior research has linked participation in undergraduate career planning courses to better outcomes for students (Folsom et al., 2004; Osborn et al., 2007; Parks et al., 2012; Reardon et al., 2015). Moreover, prior research has established relationships between STEM career development and STEM outcomes (Belser et al, 2017; Freeman, 2012; Gentile et al., 2012; Prescod et al., in press); however, these studies have been limited by correlational designs and lack of a control group. As such, building research projects that incorporate a treatment-control group design into STEM career initiatives would help establish a causal link between these initiatives and STEM outcomes and fill a clear gap in the literature. As is necessary with outcome research, replication studies, particularly involving multiple research sites would help establish the efficacy of such a treatment.

In prior research studies, researchers highlighted additional variables related to STEM outcomes that may be of interest to career researchers. Lent et al. (2016) noted links between retention and both intended persistence and self-efficacy for engineering students. Lent et al.

(2008) also incorporated self-efficacy, outcome expectations, and demographics into a retention model. Other researchers have established that internal processes specific to gender and ethnic minority students (e.g. stereotype threat, gender stereotyping, math anxiety) also relate to STEM outcomes (Beasley & Fischer, 2012; Cundiff et al., 2013; Litzler et al., 2014). Incorporating these elements, which have more commonly been applied to higher education and STEM research, into career development models may help account for more variance in STEM outcomes. Moreover, additional career assessments based on other career theories (e.g. the Strong Interest Inventory, the Career Development Inventory) can provide additional career specific information to models.

The findings of this study indicated that students who have a more solidified major before starting college have higher odds of being retained in STEM majors. School counselors are uniquely positioned to be a part of collaborative STEM career development work, as they are already charged with providing career development programming in their school settings (Curry & Milsom, 2014). Researchers can partner with school counselors to develop STEM career initiatives that would allow for conducting outcome-based research with such interventions. These investigations could focus on how such interventions impact math and science test scores, math and science self-efficacy, and entry into the STEM pipeline.

Implications

In the following sections, the researcher presents the practice implications that these research findings have for professionals in varying settings.

Implications for Higher Education

Higher education professionals can range from coordinators of STEM programming to University administrators charged with making decisions. The findings of this study provide evidence that the variables explored do matter with regard to STEM recruitment and retention. Based on the result indicating that STEM-decided students have better retention outcomes, those in charge of STEM programming should strive to provide opportunities for students to solidify their major decision, rather than simply providing opportunities for students to be exposed to STEM fields. Structured career development programming, such as career planning coursework, is one strategy for helping students choose an appropriate major. Whereas the effect sizes (as measured by the odds ratios) were small for the CTI change scores, these scores, which represent improvements in negative career thinking, were related to increased likelihoods of being retained in STEM majors.

Similarly, undergraduate STEM programming also must incorporate elements aimed at rectifying demographic underrepresentation in STEM fields, which should be an on-going process rather than a one-time event (i.e. exposing students to academic and professional mentors that challenge gender stereotypes, rather than just having a one-time guest speaker from an underrepresented group). As the influence of gender and ethnicity changed with the 2nd year and 3rd year retention outcomes, professionals managing such programming should take note that services aimed at mitigating the effects of demographic representation may be most effective when they are continuous throughout students' academic journeys, rather than contained within the first year of college. Although math supports are commonly included in these efforts, programming should also be sensitive to interactions between demographics and mathematics. A final recommendation is that STEM recruitment and retention programs should include a

professional with knowledge of career development processes and practice on planning and decision making teams to help ensure that career development theory and empirical research are considered. As these programs translate into costs paid by grants, foundations, or university budgets, ensuring that programming incorporates best practices may provide a more cost-effective solution.

Implications for College Counseling and Advising

College counselors and advisors have a front line role in helping students matriculate through degree programs; moreover, they often work with students who are struggling to decide on a major or career path. As the previous section noted, special attention should be paid on helping students solidify their major early, as this study demonstrated better STEM retention outcomes for students who came into college with a declared STEM major. Counselors and advisors should also ensure that their work and programming is sensitive to demographic stereotypes and representation needs; exploring these topics with students in individual meetings may help students work through problematic thinking in these areas. Moreover, these professionals should utilize assessment data and research on assessment data to connect students with additional resources. Related to math, students' scores on math assessments may translate into increases or decreases in the odds of successfully completing a STEM major; as such, counselors and advisors can help students with lower math scores to identify available math supports at the university. Similarly, career readiness assessments like the CTI may help career counselors and advisors tailor their approaches to students' individualized needs.

Implications for School Counseling

The findings of this study make a strong case that having a decided major prior to entering college can translate into a higher likelihood of being retained in a STEM major. Coupling these findings with Gottfredson's (1981) research indicating that children begin to eliminate career options early in life, it is apparent that career development work must begin in the K-12 setting. Mansfield et al. (2014) echoed this need for STEM-specific career development work at the K-12 level in order to effectively address underrepresentation of females and ethnic minorities within STEM. School counselors are often the only professionals on school campuses with career development training, and as such, they can play a critical role in providing interventions for students related to STEM careers. However, as they may not have received specific training on STEM initiatives, school counselors can partner with math and science teachers, as well as members of the community, to help marry career development knowledge with industry-specific knowledge. In addition, as mentioned in the research implications, school counselors can serve as a gateway for researchers to investigate STEM initiatives in the K-12 arena. These partnerships can serve to further the science of career development and provide a critical service to students.

Implications for Counselor Education

The present study also has significance for counselor education. From a research perspective, counseling literature focused on STEM initiatives has primarily been discussed in relation to K-12 settings with school counselors and largely has not been empirically based. However, the program within this study is a unique collaboration in which individuals from counselor education brought career development expertise to a higher education STEM

initiative. With such interdisciplinary partnerships, counselor education researchers can provide critical knowledge and expertise in the area of career development that can impact STEM retention. Additionally, these partnerships translate into potential external funding. Though federal science agencies, such as the National Science Foundation, have supported counselor education researchers, these projects have rarely been in the area of STEM career development, particularly involving a career related intervention (NSF, 2017). As such, the findings of the present study can serve as a foundation for future evidence-based outcome research involving STEM career initiatives.

In addition to research initiatives, counselor educators also need to ensure that their counselors-in-training are exposed to information about STEM fields in their career development coursework. As these trainees include future school counselors, college counselors, and career counselors, this information would represent current research that can translate into benefits for future clients. Specifically, counselors-in-training need to be aware of trends in STEM fields, interventions and assessments that work, and the unique needs of marginalized populations with regard to some industries like STEM where they are underrepresented. With the current and projected deficits in STEM fields, a new generation of STEM-informed helping professionals would be uniquely positioned to make a difference in these outcomes.

Implications for Public Policy

In line with implications for counselor educators and counseling professionals, these findings provide implications for public policy as it relates to preparing students to be college and career ready. As the findings highlighted the importance of major decidedness prior to reaching college, policies and initiatives should reflect this need. Government agencies that

emphasize STEM (e.g., the NASA Education Office) should continue to provide programming aimed at bolstering interest in STEM careers for children and adolescents through summer camps, online media, and outreach. These types of initiatives could also be factored into afterschool programming. To provide support for career planning in public schools, teacher education programs could incorporate career development training into their preparation programs. Moreover, as school counselors are uniquely trained to do this work in education settings, governing bodies and school boards should explore avenues to adequately staff school counselors in schools and remove ancillary duties from school counselors to maximize their ability to provide career development programming.

Partnerships between K-12 and the STEM industry private sector exist currently, but these collaborations could be strengthened to provide more targeted support. Another possible solution is to increase students' access to internships and apprenticeships in high demand career fields within high school curricula. These hands-on experiences have shown efficacy in existing programs, such as the Swiss Vocational and Educational Training System that integrates apprenticeships within the education system (Hoffman & Schwartz, 2015). As a variation of this initiative will be piloted in Colorado in 2017, other states could utilize the findings and outcomes of both the Swiss and Colorado programs to model similar approaches (CareerWise Colorado, 2017). In essence, the findings of this study, as well as other studies on STEM initiatives, should not only inform future research, but should also factor into decisions made regarding future programming.

Summary and Conclusion

The purpose of this study was to determine the degree to which demographic variables, math ability, and career development factors could predict undergraduate retention in STEM for participants in a STEM recruitment and retention program. Based on prior studies and existing literature, this study built upon existing literature related to gender, ethnicity, and mathematics and added to the literature regarding career initiatives within STEM fields. Using binary logistic regression, the researcher explored these variables with first to second year STEM retention and first to third year STEM retention. The analyses revealed that students who had a declared STEM major prior to starting college were consistently more likely to have a higher likelihood of being retained in a STEM major. Students participating in a STEM Seminar course (representing a higher level of major decidedness) were also more likely to be retained in a STEM major than initially undecided students participating in a STEM-focused career planning course. Ethnicity was a significant predictor of STEM retention with most of the models; however, the results varied on which specific subgroups were more likely to be retained. Gender was only a significant predictor in one model, unlike existing literature, but these outcomes may relate to program elements or sampling bias. Higher math scores (either measured by the SAT Math subtest or the UCF Math Placement--Algebra test) also predicted greater odds of being retained. Finally, change scores from the Career Thoughts Inventory, showed an inconsistent ability to predict outcomes, although the directionality of their predictions mostly matched with prior research.

The results of this study have implications for researchers, higher education professionals, and counseling professionals in varying settings. Each of these identified players can utilize the findings of this study to make more informed decisions about STEM initiatives in

their respective settings. Moreover, the implications for this study serve as a call for a multidisciplinary approach to solving problems within STEM career attainment. Coupling innovative and impactful STEM career research with empirically-sound STEM initiatives may be the driving force in improving STEM outcomes from K-12 to the workforce.

APPENDIX A: IRB APPROVAL

University of Central Florida

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Cynthia Y. Young** and Co-PIs: **Andrew P. Daire, Christopher Parkinson, Melissa D. Dagley, Michael Georgiopoulos**

Date: **April 13, 2012**

Dear Researcher:

On 4/13/2012, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review:	Exempt Determination
Project Title:	COMPASS (Convincing Outstanding-Math-Potential Admits to Succeed in STEM) Project Description
Investigator:	Cynthia Y Young
IRB Number:	SBE-12-08370
Funding Agency:	National Science Foundation
Grant Title:	COMPASS (Convincing Outstanding-Math-Potential Admits to Succeed in STEM) Project Description
Research ID:	1053127.

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Joanne Muratori on 04/13/2012 05:00:51 PM EDT

Joanne Muratori

IRB Coordinator

APPENDIX B: COMPASS CONSENT FORM

Consent Form

Print Name: ____

PID: _______________________________

I have read the "Informed Consent to Participate" and agree to allow Dr. Cynthia Young and Dr. Michael Georgiopoulos to use the information I provide to conduct their research titled '**COMPASS** (**C**onvincing **O**utstanding-**M**ath-**P**otential **A**dmits to **S**ucceed in **ST**EM)

I am 18 years or older □ ▯

Signature ____ Date _______________

If under 18, please have parent or guardian sign as well:

Signature ____ Date _______________

APPENDIX C: COMPASS INFORMED CONSENT

INFORMED CONSENT TO PARTICIPATE
COMPASS (**C**onvincing **O**utstanding-**M**ath-**P**otential **A**dmits to **S**ucceed in **S**TEM)

A research project is being conducted at the University of Central Florida and funded by the National Science Foundation on student learning in Science, Technology, Engineering and Math (STEM) by **Dr. Cynthia Young (College of Sciences) and Dr. Michael Georgiopoulos (College of Engineering and Computer Science) and other investigators** at the University of Central Florida. The purpose of the study is to recruit students into STEM disciplines and then positively influence them to persist in STEM and eventually become successful scientists and engineers by emphasizing their math competitiveness and other important skills such as communication, teamwork, active involvement in research, and experiential learning.

You are being asked to take part in this study by completing surveys and questionnaires throughout the program. Some of the surveys will be sent to you as e-mails and will take approximately 15 minutes of your time. To determine changes in career readiness that occur, assessments will be tracked throughout the course. Other questionnaires will be completed during class by your instructor. These surveys will take approximately 15 minutes of class time. This will allow us to collect information for feedback within the program and relate it to content specific work. Please be aware that you are not required to participate in this research and you may discontinue your participation at any time without penalty. You may also omit any items on the questionnaires or surveys you prefer not to answer.

There are no risks associated with participation in this study. If you have further questions about your rights, information is available from the contact person listed at the end of this consent form. Your responses will be analyzed and reported by an external assessor to protect your privacy. If you agree to voluntarily participate in this research project as described, please indicate your agreement by completing and returning the attached consent form. Please retain this consent cover letter for you reference, and thank you for your participation in this research.

Institutional Review Board (IRB)
University of Central Florida (UCF)
12443 Research Parkway, Suite 207
Orlando, Florida 32826-3252
Telephone: (407)823-2901

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