A LONGITUDINAL STUDY OF THE INFLUENCE OF A STEM CAREER PLANNING COURSE AND PERCEIVED STRESS ON CAREER SEARCH SELF-EFFICACY AND RETENTION IN ENGINEERING UNDERGRADUATE STUDENTS

Autumn Randell

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A dissertation submitted in partial requirements for the degree of Doctor of Philosophy in Education with a concentration in Counselor Education and Supervision at Virginia Commonwealth University

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ACKNOWLEDGEMENT

First, I would like to thank God, it is through him all things are possible. He gave me strength, patience, and discernment along this Ph.D. journey and he will continue to guide me as I embark on this next chapter of my life. Next, I would like to thank my loving husband, Ken. You supported me through all of the sleepless nights and encouraged me to finish what I started even when times were hard, frustrating, and overwhelming. I would not have made it through this program without your encouragement and strength. You support my purpose and I am forever grateful for the supportive role you played during this time in our lives. I want thank my family and friends. My mother and father instilled in me the importance of education from a young age. Without the values they instilled in me, I would not have dreamt that I could get a Ph.D. Thank you for giving me access to educational opportunity and making sure that I had what I needed to focus on school. My line sisters, Tracy, Bianca, Brittany, Janell, and Joyce, thank you for always listening to my frustrations and encouraging me to walk in my purpose. You each inspire me. All of my friends, especially, Patrice, Alex, Bre, and Kayla, thank you for checking in on me, offering healthy distractions, visiting me, and motivating me throughout my time in this program. I had several mentors along the way. Thank you, Dr. Steen, who wrote my letter of recommendation for admission to this program as well as Dean Daire, Dr. Hopp, and all the Holmes Scholars. Thank you for your feedback, advice, professional development, and guidance. I would not be the counseling and counselor education professional that I am today
without all of your help. In addition, I had the opportunity to go through this journey with a
group of people. To my cohort, Nick, Ila, Lindsay, Jonathon, Suzanne, and Michael, thank you
for all of the laughs, engaging discussions, and collaborations. I look forward to seeing all the
amazing and impactful things that you each will do in the future. I could not have picked a better
group of people to complete this journey with me. Next, thank you to all of my dissertation
committee members. My dissertation chair, Dr. Gnilka, thank you for supporting me from day
one, allowing me to develop as a researcher; supervisor; and counselor educator. You have been
a monumental part of my development and growth. I have always valued your feedback. To my
committee member, Dr. Prescod, thank you for laying the foundation for me to complete this
dissertation. Your work was critical to the development of this project. I look forward to
collaborating with you in the future and I value your insight. Dr. Johnson, thank you for your
enthusiasm, critical feedback, and encouragement. Your work ethic is inspiring and I am so
thankful to have you in my corner. Dr. Broda, thank you for your instruction and help. Taking
your classes has been incredibly helpful in my understanding of statistics. I will keep my notes
from your class throughout my career. I admire the passion and energy you bring to teaching and
I hope you emulate those qualities as an instructor. Last, but certainly not least, thank you to my
coworkers at Engineering Career Services, Anita, Laura, Tiffany, Michelle, Rebecca, Tonia and
Carolyn. Thank you for taking a chance and hiring me. I am so thankful for the opportunity to
grow as a counselor by interacting with engineering students. I am also so proud that I got to be a
member of such a powerful team of women. My dissertation would not be possible without the
opportunity you all gave me. Thank you for everything! The work you do matters.
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A LONGITUDINAL STUDY OF THE INFLUENCE OF A STEM CAREER PLANNING COURSE AND PERCEIVED STRESS ON CAREER SEARCH SELF-EFFICACY AND RETENTION IN ENGINEERING UNDERGRADUATE STUDENTS

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Virginia Commonwealth University, 2020

Chair: Dr. Philip Gnilka
Associate Professor, Department of Counseling and Special Education

This study investigated a) the influence of a STEM career planning course on undergraduate engineering students’ career search self-efficacy (CSES), b) the influence of perceived stress on building students’ CSES, and c) the relationship CSES had in predicting students’ odds of persistence in an engineering major. The researcher analyzed students’ pre- (week 1), mid- (week 6), and posttest (week 14) scores of CSES and perceived stress. Data were collected from the Spring 2019 and Fall 2019 cohorts of a STEM career planning course. Participants completed an online survey which included a demographic questionnaire and measures of perceived stress and CSES.
The analysis included \((N = 286)\) undergraduate engineering students. Repeated measures multilevel models and a logistic regression were analyzed to answer the study’s research questions. According to the results of the multilevel model, after accounting for perceived stress, students’ CSES increased over the semester in a STEM career planning course. Further, perceived stress was a significant, negative predictor of CSES scores over the course of the semester and the results of the logistic regression analysis suggested that CSES was a significant, positive predictor of students’ increased odds of persisting in an engineering major.

As an exploratory analysis, this study examined changes in CSES scores based on demographic variables including race, gender, ethnicity, and first-generation status. However, changes in CSES scores over the course of the semester did not significantly vary based on the aforementioned demographics. Additionally, this study included another exploratory multilevel model analysis with career advising ratings and mock interview appointment ratings as predictors of CSES over the course of the semester. The results yielded a statistically significant positive relationship between career advising ratings and CSES scores at each timepoint. Overall, the results of the study support STEM career planning courses as impactful interventions for undergraduate students. Specifically, this STEM career planning course was associated with positive self-efficacy and persistence outcomes. In addition, this study provided insight into how career counseling interventions can positively influence career development outcomes for students in STEM career planning courses. Implications for future research; school and career counselors; and counselor education are discussed.
Chapter One
Introduction

Science, Technology, Engineering, and Mathematics (STEM) professions have been vital to the United States of America’s (U.S.) economy since the establishment of West Point in 1802. West Point graduates often designed and built the railroad systems, roads, and bridges that were vital to the nation’s expansion (Jolly, 2009). In addition, triumphs in STEM industries have been longstanding indicators of the U.S. global standing (Friedman, 2005; Jolly, 2009). The impactful role that STEM professions have played in the U.S. economy is illustrated in the federal government’s dossier of investments in STEM industries, education, and initiatives. For instance, the Morrill Act of 1862 was the first federal attempt to provide post-secondary funding to support agriculture, home economics, and mechanical arts programs (Butz, Kelly, Adamson, Bloom, Fossum, & Gross, 2004). The Morrill Act of 1862 also provided support for science and engineering industries and indirectly led to the establishment of research-based university systems (Butz et al., 2004).

Related, the Morrill Act of 1862’s federal funding for STEM programs paralleled the STEM initiatives funded during the launch of the 1957 Soviet Sputnik (Friedman, 2005). During this time, the U.S. was in a “quiet crisis” over its ability to compete globally in space exploration (Friedman, 2005; Jolly, 2009). The Soviet Union’s 1957 launch of Sputnik which orbited around earth for 98 minutes, led to competition to enhance the STEM technical skills in the U.S. workforce (Jolly, 2009). This competition surrounding space exploration exposed short-
comings in the educational services offered in U.S. As a result, the federal government developed funding reforms across all levels of the country’s educational system. Thus, in 1958, the federal government aimed to counteract the Soviet Union’s superior education systems by passing the National Defense Education Act to develop an elite pipeline of STEM professionals in the workforce.

Unfortunately, the disparities in the STEM workforce that were present since the formation of West Point and the beginning stages of space exploration, are still present today. Thus, more recently, both President Barack Obama and President Donald Trump signed legislation that provided federal funding aimed at increasing and diversifying the number of people entering the STEM workforce (Education, 2017; Educate to Innovate, 2009). Even though there is still the pressing need for STEM professionals in the U.S. workforce, there is a lack of post-secondary students entering and staying in STEM majors until graduation. Almost 50% of undergraduate students who begin in a STEM major do not complete their STEM bachelor’s degree (Chen, 2014). To make matters worse, these post-secondary retention rates are disproportionately lower for racial minorities (i.e., Black, American Indian, and Latinx) and women interested in STEM fields (Carson, 2017; National Center for Science and Engineering Statistics [NCES], 2019). Overall, the high attrition rates among undergraduate students majoring in STEM and the lack of diversity in STEM post-secondary education perpetuates large gaps in the STEM workforce (NCES, 2019; Randstad USA, 2018).

Thus, over the last 25 years many universities have been pressured to develop interventions and initiatives which increase the number of students entering and staying in STEM majors until graduation. Some of these STEM-focused post-secondary initiatives include: a) STEM living learning programs in which small groups of undergraduates majoring in STEM
live near each other and are given academic and social supports (Brower, Inkelas, & Crawford, 2004); b) STEM summer bridge programs—in which small groups of incoming undergraduate students receive academic interventions before starting their college journey (Ashley, Cooper, Cala, & Brownwell, 2017); and c) STEM career planning courses which are credit bearing course that promote the career development, career exploration, and career decision-making of undergraduate students majoring in STEM (Belser, Prescod, Daire, Dagley, & Young, 2017; Folsom, Peterson, Reardon, & Mann, 2005).

Although STEM summer bridge and living learning programs have gained traction at universities, they each have several downsides. Both programs only help a small number of students. Often, STEM summer bridge programs only have capacity to help small groups of high achieving minority students who want to major in STEM fields during college (Ashley, Cooper, Cala, & Brownwell, 2017). Additionally, the evidence-based research that connects these interventions to positive outcomes (i.e., increases in students’ major retention) is limited and these interventions show inconsistent long-term impacts (Ashley, Cooper, Cala, & Brownwell, 2017; Soldner, Rowan-Kenyon, Inkelas, Garvey, & Robbins, 2012). However, more recently the “STEM Crisis” has been looked at from a career development perspective. Interestingly, career development interventions such as STEM career planning courses are shown to increase students’ odds of retention in STEM majors and reduce their negative career thoughts (Belser et al., 2017; Prescod, Daire, Young, Dagley, & Georgiopoulos, 2018).

Belser et al. (2017; 2018) and Prescod et al. (2018) studies were the first to examine how these STEM-focused career planning courses improved students career development and retention in STEM majors. However, their work mainly focused career development factors such
as negative career thoughts. Yet, there are other ways in which STEM-focused career planning courses may enhance students’ career development.

**Missing Literature and the Purpose of the Study**

For instance, self-efficacy contributes to students’ motivation to persist in completing their STEM degree (Graham, Frederick, Byars-Winston, Hunter, & Handelsman, 2013). Self-efficacy is one’s belief in their ability to influence and control the events that happen in their life and self-efficacy beliefs are tailored towards specific domains or interests (Bandura, 1994; 2006). In addition, self-efficacy is molded by several different learning experiences including mastery experiences, vicarious learning, verbal persuasion, and physiological arousal (e.g., stress and anxiety; Bandura, 2008). Mastery experiences build one’s domain-specific self-efficacy by allowing a person to experience tasks first-hand in order to accomplish a challenge. Moreover, vicarious learning, involves seeing people similar to oneself show consistent effort towards accomplishing a goal which in turn builds one’s belief in their own ability to accomplish a similar goal. Likewise, verbal persuasion builds self-efficacy through other people helping an individual believe that they are capable of reaching their goals. These verbal persuasions can be positive appraisals such as telling a person “you can do this.” Lastly, physiological arousal impacts self-efficacy because changes in one’s emotions, mood, and physiological state, positively or negatively, impact a person’s belief in their ability to perform tasks. In particular, high levels of stress and anxiety negatively impact a person’s self-efficacy and ability to set and accomplish goals (Bandura, 1986).

Additionally, self-efficacy is related to several domains and tasks. In relation to career development, one example of career-related self-efficacy is career search self-efficacy (CSES) or persons’ belief in their ability to perform career selection tasks such as exploring their personal
interests, interviewing for jobs, networking, and searching for jobs (Solberg et al., 1994). Further, CSES is influential to the present study, because the current investigation utilized a Social Cognitive Career Theory (SCCT) perspective to analyze the impact of a STEM career planning course on undergraduate engineering students’ CSES and retention while also accounting for the influence of physiological responses (i.e., stress).

Prescod et al.’s (2018) study examined the impact of a STEM career planning course on undergraduate engineering students’ career thoughts. However, no studies have examined the impact of a STEM career planning course on undergraduate engineering students’ career-related self-efficacy (e.g., CSES). However, Miatta (2013) found that participating in a general career development course increased undergraduate students’ CSES. Even so, the study had several limitations. For instance, Miatta’s (2013) study a) was a cross-sectional design, b) did not emphasize STEM career choices, and c) did not focus solely on undergraduates in STEM majors.

Moreover, none of the literature on career planning courses, specifically STEM career planning courses, emphasize the influence of mental health factors on students’ career development and retention in a STEM major. Though not specific to STEM post-secondary populations, Baghurst and Kelley (2014) looked at changes to 531 college students’ perceived stress, test anxiety, and personal burnout after receiving stress interventions during a semester of a course. Students received various stress interventions including lectures; aerobic activities; physical activities; cognitive–behavioral exercises; mental and physical relaxation strategies and practice; and exercise and wellness participation. Analysis of students’ pre and post-test scores of perceived stress, test anxiety, and personal burnout showed that students who received stress management interventions and physical activity interventions over the course of a semester
showed the greatest reduction in their stress-related post-test scores. Thus, Baghurst and Kelley’s (2014) study highlighted the need for class-based interventions that address influence of stress on college students over the course of a semester. In order to fill gaps in the literature, the current study used longitudinal data taken from a STEM career planning course class to explore the temporal nature of CSES and stress.

Further, stress is a key concern for undergraduate students (Dyson & Renk, 2006). In 2018, the American College Health Association (ACHA) reported that most undergraduate students experience symptoms of stress and stress is a major impediment to academic performance. In addition, research has shown that life stress is associated with lower levels of career decidedness and satisfaction with career choice (Bullock-Yowell, Peterson, Reardon, Leicrer, & Reed, 2011). Likewise, college can be a stressful time for undergraduate students and increases in stress can lead to poor academic achievement (Britt, Mendiola, Schink, Tibbetts, & Jones, 2016). Even so, psychological factors (e.g., stress) are not frequently studied in relation to the career development of undergraduate students majoring in STEM (Park et al., 2019). Therefore, this study sought to explore the temporal relationships between undergraduate engineering students’ stress and CSES in order to contribute to the scarce literature surrounding the role of stress and career-related self-efficacy in college students majoring in STEM fields.

**Theoretical Framework**

There are several theoretical approaches that can be used to understand the intersection of career development and positive post-secondary outcomes for students majoring in STEM. In order to account for the role of self-efficacy, this dissertation study used SCCT- a theoretical perspective developed from Bandura’s Social Cognitive Theory (SCT) to explain the role of self-efficacy and contextual factors during one’s career development (Lent, Brown, & Hackett, 1994). The goal of SCCT is to help people make a career choice (Brown & Lent, 1996). SCCT
posits that making a career choice is a cyclical process in which people receive information to fuel feedback loops (Lent, 2005).

These feedback loops are explained in the interest, choice, and performance models of the SCCT framework (Lent, 2005). First, the interest model highlights that career choice is molded by self-efficacy and outcome expectations. Next, the choice model emphasizes that career choice is not a static process; rather, it is guided by individuals’ goals, action towards their goals, and their experience trying to obtain career goals. Lastly, the performance model of SCCT highlights that people’s performance attainments relate to their educational and work success as well as the degree to which they persist towards their career goals when faced with adversity.

In relation to the aims of this study, these SCCT models have been empirically supported in post-secondary populations. Specifically, SCCT has been empirically studied in engineering undergraduate students. For example, Lent and colleagues (2016) found that self-efficacy is an important pathway to students’ academic persistence in their engineering major. In studies which explore SCCT with post-secondary students, self-efficacy is an important factor to developing their STEM career choices and goals (Lent et al., 2008). However, the research that supports SCCT as an approach to understand the career interests, choices, and goals of undergraduates in majoring STEM, does not include an intervention aimed at supporting students’ career choice and retention in their engineering major. Thus, this study sought to build on previous STEM-related SCCT research to examine how a SCCT-based intervention (i.e., VCU-COE Professional Development) can build students’ CSES and predict their retention in an engineering major.
Statement of the Problem

The issue of STEM retention is critical in the U.S. and the Virginia Commonwealth University (VCU). According to publicly shared data, as of the Fall 2013 semester, the four-year graduation rate for undergraduate engineering students is 35.7% (Institutional Research and Design Support, 2019). Additionally, the five-year graduation rate (50.8%) for undergraduate engineering students is also concerning to the College of Engineering (VCU-COE) faculty and staff. Thus, the VCU-COE was in need of impactful solutions to mitigate this retention issue. Consequently, the College of Engineering Career Services Department offered a STEM career planning course. To date, the VCU-COE has not explored the influence the course has in building students’ career-related self-efficacy and improving in retention. Thus, a knowledge gap existed between what is being done in this course and how the course helps students’ career development.

The Intervention

The VCU-COE STEM career planning course is a 1-credit hour, semester long course that meets twice a week for 50 minutes. During the course students made an appointment with a career counselor; conducted mock interviews; attended employer guest lectures; networked with professionals in their field; developed a resume; and completed other career exploration and career search tasks. The course is strongly aligned with SCT, SCCT, and CSES tenets (see Table 2). It was the instructor’s intention to foster students’ career development and professional identity through experiential learning and reflective practices. The course objectives were to help students:

- Gain an understanding of the professional development opportunities and career pathways available to College of Engineering students and graduates
• Develop an understanding of employer expectations for professional and ethical behavior

• Gain an understanding of and prepare for the job search and hiring process

• Develop communication skills necessary for a successful job search and for working in a professional environment

• Develop an understanding of the benefits of networking and life-long learning

**Research Questions**

Based on the previous literature and the purpose of this study the research questions and hypotheses are as follows:

RQ1: Over the course of a semester in a STEM career planning course, is there a change in scores on career search self-efficacy?

\( H_0: \) There will be no change in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy.

\( H_a: \) There will be at least a change in early (week 1), mid (week 6), and end-of-semester scores (week 14) on career search self-efficacy.

RQ2: Will early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy vary based on undergraduate engineering students’ perceived stress?

\( H_0: \) There will be no differences between in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy based on undergraduate engineering students’ perceived stress.

\( H_a: \) There will be differences between in early (week 1), mid (week 6), and end-of-semester (week 14) on career search self-efficacy based on undergraduate engineering students’ perceived stress.
$H_0$: There will be significant decreases in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy based on undergraduate engineering students’ perceived stress.

$H_c$: Decreases in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy will vary over time depending on undergraduate engineering students’ perceived stress.

RQ3: Do undergraduate engineering students’ career search self-efficacy scores predict students’ odd of persisting in their major for the following semester?

$H_o$: Career search self-efficacy scores will not significantly predict students’ odd of persisting in their major for the following semester.

$H_a$: Career search self-efficacy scores will significantly predict students’ odd of persisting in their major for the following semester.

$H_b$: Higher career search self-efficacy scores will increase students’ odd of persisting in their major for the following semester.

**Methodology**

This study utilized a repeated measures quasi-experimental, quantitative single group pre-, mid-, and post-test design to examine differences in the studies variables overtime. Additionally, this study used secondary data gathered from the Spring 2019 and Fall 2019 semesters of a STEM career planning course. Data were collected at weeks 1, 6, and 14 using Research Electronic Data Capture (REDCap) a secure web-based application designed to support data capture for research studies (Harris, Taylor, Thielke, Payne, Gonzalez, & Conde, 2009). The measures included in the study were: the Career Search Self- Efficacy Scale (CSES; Solberg et al., 1994); the Stress Overload Scale-10 (SOS-10; Amirkhan, 2018) Personal Vulnerability (PV).
subscale; and a demographic questionnaire. Lastly, a repeated measures MLM was used to answer RQs1-2 and a logistic regression was used to answer RQ3.

**Conclusion**

This study sought to add to the literature regarding career development interventions aimed at addressing the needs of post-secondary students majoring in STEM disciplines. To do so, this study used a SCCT perspective, emphasized the role of self-efficacy, and explored the influence of stress. Research of this kind can help counselors play an active role in addressing the “STEM Crisis” in the U.S. Moreover, Estrada and colleagues (2016) developed recommendations to increase the research surrounding increasing the diversity of talent along STEM pipelines. Among these recommendations, were implementing STEM-focused interventions that are data-driven and include: comparison groups; longitudinal tracking; large sample sizes; and collection of information that tracks important outcomes (i.e., retention and persistence). Though this study did not have a control group, this study contributes to the literature regarding STEM career planning courses as impactful strategies by utilizing outcome-driven data, longitudinal tracking, and a large sample of STEM undergraduate students. The following sections in this dissertation include Chapter Two- a review of the literature on post-secondary STEM initiatives, career development theory, and gaps in the literature regarding the study’s variables. Next, in Chapter Three, the study’s design, procedures, and proposed statistical analysis are explained. Finally, Chapters Four and Five respectively, include the results and discussion sections of this dissertation.
Chapter Two
Literature Review

Overview of Related Areas

Every year there are gaps in the STEM labor markets (NCES, 2017). In 2016, the U.S. had roughly 3 million more vacant jobs in STEM fields than it had people to fill them (Randstad USA, 2018). These vacancies in the STEM workforce are perpetuated by the tendency of young people to opt out of higher-level STEM coursework (Randstad USA, 2018). For example, in 2014, Chen released a seminal report for the National Center for Education regarding STEM attrition rates in the U.S. Between 2003-2009, 48% of students earning a bachelor degree in STEM fields and 69% of students earning an associate degree in STEM fields left by spring 2009. About half of those who left, switched their major to a non-STEM field, and the rest left STEM fields by leaving college before earning a degree or certificate. Furthermore, Chen (2014) discussed that when compared with other countries, the U.S. has one of the lowest ratios of STEM to non-STEM bachelor degrees. Related, despite the important role STEM fields have in the U.S. economy, students who have strong potential in STEM often avoid entering careers in critical STEM areas. The American Society for Mechanical Engineers (ASME) explained that the U.S. cannot afford to lose anyone with technical skills in STEM areas because people with these skillsets create sustainable futures for the nation, improve health, and enhance cybersecurity (Crawford, 2012).
The conversations surrounding the shortages in the STEM workforce are often discussed in broad terms. However, Xue and Larson (2015) explained that while shortages do exist in the STEM workforce, so do surpluses. For example, there in 2011 there were 600,000 unfilled manufacturing jobs that required STEM technical skills. Conversely, there is a surplus of STEM talent in biomedical and chemistry Ph.Ds. For graduates in biomedical and chemistry disciplines, entering the STEM workforce has gotten more difficult due to the downsizing of biotechnology, chemical, and pharmaceutical jobs. Surprisingly, since 2000, pharmaceutical companies in the U.S. have cut 300,000 jobs. However, the unemployment rates for individuals in computer disciplines have significantly declined due to the increased demands in both the federal and public sectors. Overall, yes, there is a “STEM Crisis.” However, it is important to understand the STEM industries are heterogeneous and not all STEM majors were equally in demand at all times and in all sectors of the U.S. economy. This literature review will focus on data related to STEM bachelor’s degrees, because there is an increased need for STEM professionals with bachelor’s degrees.

In 2015-2016, more bachelor’s degrees were awarded to females (58%) than males (42%); yet, females only made up 36% of bachelor degrees in STEM fields (NCES, 2019). Overall, woman earn less bachelor degrees in STEM (Buntz, 2014). However, according to the American Society for Engineering Education, women earn 39% of biomedical engineering bachelor degrees. Thus, biomedical engineering has the highest percentage of woman when compared to other engineering disciplines. Yet, even for biomedical engineering- women are still underrepresented in the workforce. To some extent, the lack of woman earning STEM bachelor degrees and entering the workforce may be due to stereotype threat. Beasley and Fischer (2012) explored the role of stereotype threat on student’s decision to declare a STEM major. They hypothesized that the reason why women were significantly more likely to leave
their STEM major might have been due to stereotype threat - the anxiety produced by the anticipation of being judged. Similarly, Black students pursuing STEM degrees experience stereotype threat stemming from racist ideals about their reduced capacity to thrive in STEM coursework (Gasman & Nguyen, 2019).

Likewise, only 28% of STEM employment is held by non-white individuals (Dailey & Eugene, 2013). Although Black, American Indian, and Latinx populations are expected to make up approximately 40% of the U.S. population by 2050, these racial/ethnic groups are underrepresented in STEM fields (National Action Council for Minorities in Engineering [NACME], 2014). For example, in 2010, URM made up only 10.2% of employed engineers (NACME, 2014). According to the Higher Education Research Institute (HERI, 2010), the proportion of white and URM students interested in STEM has converged over the past 40 years; however, the numbers related to STEM degree attrition has diverged. The overall attrition rates in STEM fields are high, but are even higher for URM (Rask, 2010). For instance, of the 1.8 million bachelor degrees awarded in 2015-2016, 331,000 (18%) of those degrees were in STEM fields (NCES, 2019). Furthermore, the percentage of Hispanic, Black, and American Indian students who completed a bachelor degree in STEM disciplines was lower than the overall percentage of bachelor degrees awarded in STEM fields that year (i.e., 2015-2016; NCES, 2019). Specifically, Black students are more likely than any other racial group to leave a STEM major or drop out of college (Estrada, et al., 2016). This tendency for unrepresented students, more specifically Black students, to not complete a degree in a STEM field may be due to the pedogeological practices that discourage minority students’ sense of belonging at universities and limit their ability to persist (Gasman & Nguyen, 2019). Many of the underrepresented students who do persist in a STEM discipline have to expend more energy and
focus than their White counterparts in order to navigate the culture of STEM at predominantly White institutions (PWI).

In sum, there is a national need for STEM graduates from diverse backgrounds to fill the millions of jobs in the STEM workforce. The combination of the limited graduates with bachelor’s degrees in STEM, professionals in the STEM workforce, and diversity in the STEM are commonly referred to as the “STEM Crisis” (Chen, 2014; Herman, 2019; Xui & Larson, 2015). In this literature review, the researcher discusses an overview of STEM initiatives that are growing in popularity on college campuses. Next, this literature review focuses on career theories that are empirically supported with post-secondary STEM populations. Following, the literature review emphasizes the role of self-efficacy in SCT and SCCT. The next section mainly highlights literature that supports the use of SCCT with STEM post-secondary populations. Then, gaps in the literature on the present study’s variables are addressed. Lastly, this literature review concludes with an overview of the relevant terms used in the current investigation.

**Federal STEM initiatives.** The continuous lack of individuals in the U.S. job market with STEM technical skills led has to federal initiatives aimed at improving students’ STEM performance and participation (Chen, 2014). In 2009, the Obama Administration launched the Educate to Innovate Initiative (Educate to Innovate, 2009). This initiative aimed to a) build a coalition of CEOs to leverage STEM opportunities in the private sector, b) prepare 100,000 new STEM teachers throughout the next decade, c) bolster federal investment in STEM, and d) increase diversity in the STEM talent pool (Educate to Innovate, 2009). Moreover, the Obama administration emphasized the importance of increasing the participation of women and racial minorities in STEM fields. Increasing the number of women and underrepresented minorities (URM; i.e., Black, Hispanic/Latinx, and American Indian adults) in STEM is imperative
because the lack of diversity in STEM fields contributes to the overall lack of STEM professionals in the workforce (NCES, 2019).

The dedication to increasing STEM professionals generally, and more specifically, increasing the number of women and URM in STEM, was also supported by the following administration. President Donald Trump signed a Presidential Memorandum to further expand STEM and computer science education (Education, 2017). This memorandum devotes 200 million dollars in federal grants per year to support STEM and computer science initiatives at the K-12 and post-secondary level. The goal of President Trump’s memorandum was also to increase access to STEM education for women, minorities, and students in rural areas. Women make up 47% of the labor market (Carson, 2017). Even so, women comprise only 25.6% percent of computer and mathematical occupations, 15.4% of architecture and engineering occupations, and 18% of computer science degrees women. As a result of the disparities between the entrepreneurship of women in STEM, President Donald Trump signed the Inspire Act which supports the National Science Foundation (NSF) in promoting STEM entrepreneurship for women. Also, the Inspire Act supports the National Aeronautics and Space Administration (NASA) in encouraging women to pursue STEM careers in aerospace.

Post-secondary STEM attrition and initiatives. The “STEM Crisis” is alarming to the federal government, scholars, and policy makers due to the growing demands for diverse talent in STEM fields (Kitchen, Sadler, & Sonnert, 2018). For example, it is projected that between 2014-2024, STEM jobs will continue to grow by 8.9% (Noonan, 2017). However, undergraduate students are not completing bachelor’s degrees in STEM at rates that meet the growing need in the workforce. Many reasons for this are discussed in the literature. For instance, undergraduate students often view STEM careers as too challenging to pursue (Kitchen, Sadler, & Sonnert, 2018; Randstad USA, 2018). Related, young women tend to report
lower levels of confidence in their STEM abilities (Kitchen, Sadler, & Sonnert, 2018; Randstad USA, 2018). For the women who do go on to pursue STEM careers, they increasingly experience stereotype threat along their career journey (Beasley & Fischer, 2012). Additionally, the disparities in the STEM degrees may be due to students’ lack exposure to the career possibilities in STEM fields and the overall the lack of support for URM and women (Kitchen, Sadler, & Sonnert, 2018). As a result, there are more STEM pipeline leaks for URM and women (Estrada, et. al., 2016).

Furthermore, the high post-secondary STEM attrition rates may be due to the harsher grading practices in STEM undergraduate programs in comparison to non-STEM programs (Rask, 2010). Moreover, Chen (2015) discussed potential reasons why high achieving students leave their STEM major include: 1) the rigor of STEM coursework is too challenging for students, 2) if students are not able to take STEM coursework during their first year, they are at an increased risk for not completing a STEM degree, and 3) high achieving students might view careers in health sciences as more lucrative. Additionally, some students leave STEM majors because they do not gain active learning experiences in STEM introductory courses (Graham et al., 2013). These introductory courses are vital because they have been shown to reduce attrition. Also, the lack of connection between STEM curriculum and STEM careers might also negatively impact STEM retention (Estrada et al., 2016).

This combination of students not having access to STEM coursework early on in their program; students’ view of introductory STEM courses as uninspiring; students’ lack of exposure to STEM career opportunities; the perception that STEM is too challenging; and the lack of support for diversity and inclusion, all contribute to the high post-secondary attrition rates of STEM undergraduates and the vacant jobs in the STEM labor market (Chen 2014; Estrada, et.al., 2016; Graham, et al., 2013; Kitchen, Sadler, & Sonnert, 2018). Thus, many
universities support the development of STEM initiatives that promote STEM educational and career opportunities in order to reduce disparities in STEM degree programs. Examples of the post-secondary STEM initiatives that will be discussed in this literature review include: STEM summer bridge programs, STEM living-learning programs, and STEM career planning courses.

**STEM summer bridge programs.** Summer bridge programs are university funded programs that address the high school-to-college transition to increase the STEM pipeline (Perna, 2002; Sablan, 2014). Summer bridge programs are typically tailored for marginalized populations such as low-income, URM, and first-generation college students. These programs assume that student participation in a summer bridge program will help marginalized students become better prepared for college and in turn, increase their degree and career attainments (Kallison & Stader, 2012). However, summer bridge programs only help a small portion of incoming college students who show promise for thriving in college and may need more support during the high school-to-college transition (Douglas & Attewell, 2014; Sablan, 2014).

Although summer bridge programs only serve a few individuals, STEM summer bridge programs may positively influence students’ STEM knowledge, preparation, and achievement (Kitchen, Sadler, & Sonnert, 2018). In order to understand the impact of STEM summer bridge programs on the STEM career aspirations of college students, Kitchen and colleagues (2018) utilized data from the NSF funded Outreach Programs and Science Career Intentions (OPSCI) study. The surveys from the OPSCI study were distributed to first-year college students in 2013. The study included data from 104 public institutions from which 15,847 students completed paper surveys. The OPSCI survey included 37-items and measured students’ career plans; middle school science and math experiences; high school background; STEM-related interests; and family demographics. Of the total respondents, 383 reported that they participated in a STEM summer bridge program. In their propensity weighting analysis, gender, race/ethnicity,
standardized test scores (i.e., SAT and ACT), first generation-status, and number of math classes completed were included as controls. The results indicated that when compared with students who did not participate in STEM summer bridge programs (24%), a greater proportion (40%) of those who participated in STEM summer bridge programs reported that they aspired to enter STEM careers at the beginning of their college experience. Additionally, 40% of the students who participated in a STEM summer bridge program reported that it showed them the real-life relevance of STEM. Furthermore, 88% reported that they would recommend participating in a STEM summer bridge program to a friend. Lastly, the results of the logistic regression indicated that when compared to students who did not participate in a STEM summer bridge program, the odds of having STEM career aspirations in the beginning of college were twice as high for students who participated in a STEM summer bridge program.

Over the last 25 years, the literature on STEM summer bridge programs has grown due to the positive impacts these programs have in forming first-year college students’ STEM-related career goals (Ashley, Cooper, Cala, & Brownwell, 2017). Thus, Ashley et al. (2017) did a comprehensive literature review on STEM summer bridge programs in order to a) describe existing STEM summer bridge programs, b) identify the goals of the STEM summer bridge programs, c) highlight the success of STEM summer bridge programs, and d) provide recommendations for building future STEM summer bridge programs. The comprehensive literature review revealed that there is a need to increase peer-reviewed publications on STEM summer bridge programs and a need to further refine and report on the outcomes associated with participating in these programs. These programs help bring undergraduate students to the university in STEM majors; however, there is little empirical research on the long-term STEM retention and career attainment associated with participation in these programs. However,
STEM summer bridge programs are only one post-secondary STEM initiative aimed at increasing the number of STEM professionals.

*STEM living learning programs.* Living-learning programs (LLPs) are also growing STEM initiatives at universities. LLPs are residential communities in which undergraduate students who share a particular academic interest live together to participate various in academic and social programming (Brower, Inkelas, & Crawford, 2004). LLPs typically build student wellness and academic success by providing students with a sense of community (Brower & Dettinger, 1998). Moreover, students who participate in LLPs gain access to peers who have shared interests and specialized programming that promotes professional development and social interactions (Brower & Dettinger, 1998). In 2007, there were close to 700 LLPs nationwide and most of these programs aimed to promote wellness during the first-year-of-college transition (Soldner, Rowan-Kenyon, Inkelas, Garvey, & Robbins, 2012).

Though LLPs are increasingly popular on college campuses, there is a dearth in the literature describing the outcomes of STEM-focused LLPs. Thus, Soldner et al. (2012) aimed to investigate whether STEM-focused LLPs increased students’ persistence in STEM majors. They utilized the 2007 National Study of Living-Learning Programs (NSLLP) which surveyed 110,682 students at 46 universities across the U.S. However, their study only included a subgroup of 5,240 first-year college students (2,098 men and 3,142 women) who did, and did not, participate in their university’s STEM LLP. The participants completed the Resident Environment Survey (RES) which included 62 items related to STEM interest, faculty mentorship, peer interactions, and persistence in major. The analysis included groups of men and women in the following categories: URM (yes or no), STEM LLP vs Non-STEM LLP, and traditional residential hall. Based on these demographics, they developed a model to explain the relationship participants’
LLP participation, self-efficacy, and outcome expectations had with predicting major choice goals (i.e., persistence in STEM majors).

The results of Soldner and colleagues (2012) analysis suggested that when compared to students who stayed in a traditional residence hall during their first year, students who participated in a STEM LLP did not have an increased self-reported likelihood to complete a bachelor degree in a STEM field. Also, participation in a non-STEM LLP had a direct, negative relationship with persistence in STEM majors. Although the direct effect of the relationship participation in STEM LLPs had with STEM degree completion was not significant, the indirect effect of participation in a STEM LLP yielded a positive indirect effect on students’ self-reported likelihood of completing a bachelor degree in a STEM major. Therefore, the indirect effect of participating in a STEM LLP increased students' self-reported likelihood of completing a bachelor degree in a STEM major by 1%. Thus, these findings provided evidence that STEM LLPs are somewhat effective in supporting students’ persistence in STEM majors. Although, the results of Soldner et al.’s (2012) study provided some support for idea that participating a STEM LLP increases positive STEM persistence outcomes, there is a need to emphasize STEM initiatives that are more directly, empirically indicative of positive STEM outcomes. In addition, the effects found in this study were small; therefore, it is important to develop evidence-based post-secondary STEM interventions that have more practical implications.

STEM career planning coursework. Among the empirically supported STEM interventions are career planning courses. Over the last 25 years at universities career planning courses that support students’ career development have become increasingly more popular (Smith, Myers, & Hensley, 2002). Career planning courses are classes, taken for college credit that provide students with the problem-solving and decision-making skills needed for their career planning (Folsom, Peterson, Reardon, & Mann, 2005). These career planning courses are associated with
students seeking less withdrawals from their coursework and taking less credit hours to complete their degree. Additionally, career planning courses improve students’ career decision-making self-efficacy, especially in domains related to their belief in their ability to gather career-related information, set goals, and make future plans (Reese & Miller, 2006).

Miller, Osborn, Sampson, Peterson, and Reardon (2018) examined the impact of a three-credit-hour career planning course on the career decision states of undergraduate students. Their study included 164 undergraduate students at one university. In the course, students were encouraged to increase their self and career knowledge. In addition, students learned about social conditions that impact their career decisions (e.g., labor markets, family relationships, organizational culture) and students learned about the job search process. The participants completed three assessments at the beginning and end of the semester that measured their career decision state, career choice certainty, career choice satisfaction, and vocational clarity. The study indicated that participating in a career course allowed students to become more certain about a career choice, more satisfied with their current career choice, and more confident about the process of making a career choice.

Although research shows that career planning coursework is instrumental in improving college student’s career development, there is limited research about career planning coursework with STEM post-secondary populations. Table 1 shows the similarities and differences among general career planning courses and STEM career planning courses. It is important to develop initiatives that enhance the career development of undergraduates in STEM majors because forming a career identity increases students’ ability to make informed career decisions and increases their motivation to achieve academic success in STEM (Perez, Cromley, & Kaplan, 2014). Thus, STEM career planning courses can play an integral role in reducing STEM attrition by enhancing students’ career development.
Prescod, Daire, Young, Dagley, and Georgiopoulos (2018) explored the effects of a three-credit-hour STEM exploration course or a one-credit-hour STEM career planning course in a sample of 281 undergraduate students. The study included (n = 99) undergraduate students who were exploring STEM careers and (n = 182) students who already declared a STEM major. Students were given pre- and posttests of the Career Thoughts Inventory (CTI; Sampson, et al., 1996). The CTI is a 48-item Likert type scale assessment that measures dysfunctional or negative career thoughts. Negative career thoughts limit students’ ability to choose a career path. The results showed that both groups of students, students who had declared a STEM major or students who were exploring STEM majors, reduced their negative career thoughts during the semester that they participated in a STEM career planning course.

Moreover, when exploring the impact of participation in a STEM career planning course on STEM retention, Belser, Prescod, Daire, Dagley, and Young (2017) found that first-year undergraduate students who declared a STEM major when they participated in a STEM-focused career planning course were 17.8 times more likely to return to their STEM major during their 2nd year of college. Furthermore, students who participated in a STEM-interested career planning course and were undeclared in their first year were 15.24 times more likely to be retained in a STEM major during their 2nd year (Belser et al., 2017). However, participants were not randomly assigned to each STEM career planning course. Both Prescod and colleagues (2018) and Belser and colleagues (2017) research on the relationship STEM career planning courses have in positively impacting students’ career development and retention in STEM majors is noteworthy to the literature on career development-focused STEM initiatives. Their studies were the first to introduce career development measures in undergraduate STEM-focused career planning courses. Furthermore, Prescod and colleagues (2018) and Belser and colleagues (2017) work is seminal to the development of the current investigation, because the
present study will discuss the relationships among perceived stress, career self-efficacy, and major retention of students in a STEM career planning. Also, this study includes rigorous statistical analysis that accounts for nesting. In order to further establish context for the purpose of the current dissertation and its contribution to the literature, the theoretical underpinnings of this study must be discussed. Thus, the next section of this literature review discusses career counseling theories that have been studied with post-secondary STEM populations.

Table 1

*Similarities and Differences Among 1 & 3 Credit Hour Career Planning and STEM Career Planning Courses*

<table>
<thead>
<tr>
<th>Various Career Planning Courses</th>
<th>Similarities</th>
<th>Differences</th>
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<tbody>
<tr>
<td>1-Credit Hour Career Planning Course</td>
<td>Students learn about developing individual portfolios, exploring employment options, creating professional documents (i.e., resumes and cover letters), job searching, practicing interviewing, understanding networking, and attending various workshops (Miatta, 2013).</td>
<td>These courses are not specific to a career pathway and focus on providing students with general knowledge to inform their career decisions. Students meet for shorter periods of time each week when compared to 3-credit hour courses. Students also take career assessments (e.g. CSES). However, in Miatta’s (2013) study there was only one timepoint.</td>
</tr>
<tr>
<td>3- Credit Hour Career Planning Course</td>
<td>Students learn about the job search process, labor markets, family relationships, and organizational structures (Miller et al., 2018). Students take pre and post-test career assessments related to career decision state, career choice certainty, career choice satisfaction, and vocational clarity (Miller et al., 2018; Reese, 2006). Students set career goals and future plans (Reese, 2006). These 3-credit hour courses provide more time to process assignments in class. 1-credit hour courses might have more homework assignments to make up for the lack of time in class to create resumes, cover letters, etc.</td>
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courses are associated with positive outcomes such as increasing student decision-making skills and increasing students likelihood of finishing college (Folsom, Peterson, Reardon, & Mann, 2005).

<table>
<thead>
<tr>
<th>Course</th>
<th>Description</th>
<th>Focus</th>
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<tr>
<td>3- Credit Hour STEM Career Exploration Course</td>
<td>Students take pre and post-tests of career assessments (CTI; Belser et al., 2017). Students learn more about career opportunities in the STEM field.</td>
<td>Focus on students who are interested in majoring in STEM but are still undeclared in their major (Belser et al., 2017).</td>
</tr>
<tr>
<td>1- Credit Hour STEM Career Planning Course</td>
<td>These courses along with STEM Career Exploration courses are associated with positive retention outcomes such as increased odds of retention in a STEM major (Belser et al., 2017; Prescod et al., 2018).</td>
<td>Focus solely on students who are already majoring in a STEM area (Belser et al., 2017; Prescod et al., 2018).</td>
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Theoretical Orientation

According to the NCDA (NCDA; 2009) career counseling theory is “essential for professionals engaging in career counseling and development.” Researchers who utilize career development factors to better understand, and intervene on, various aspects of the STEM crisis use a variety of theoretical frameworks. This study utilizes a SCCT approach. However, in order to lay the foundation for this dissertation, it is important to first provide an overview of seminal career development theories that have been empirically studied with populations of undergraduate students in STEM majors.

In the Theory of Vocational Choice, Holland (1973) connected individuals’ career development to their personalities, interests, skills, and values. Holland’s theory of vocational choice purports that most people possess one of six personality types: Realistic (R), Investigative
(I), Artistic (A), Social (S), Enterprising (E), or Conventional (C; Holland, 1973). These six personality types correspond to particular physical environments that an individual would prefer to work in (Holland, 1997). For instance, those who have with a Realistic personality type tend to like work activities that require motor coordination and concrete solutions. Those with who are Investigative typically enjoy work environments that allow them to think critically and organize; while also, avoiding interpersonal situations. Additionally, those who are Artistic or Social tend desire work environments that allow self-expression and promote close relationships, respectively. Lastly, individuals who have an Enterprising or Conventional personality type tend to aspire for status and power or are concerned with rules and regulations, respectively.

Through career assessments such as the Strong Interest Inventory (SII; Strong, Donnay, Morris, Schaubhut, & Thompson, 2004), individuals can uncover their top three personality types which are represented by a three-letter code (Holland, Viernstein, Kuo, Karweit, & Blum, 1972). This three-letter code (e.g., IEC) can then be used in the Self-Directed Search (SDS; Holland, Powell, & Fritzsche, 1994) career inventory to help people learn about careers that match their personality, skills, and interests.

Holland (1997) believed that individuals search for and enter work environments that allow them to find congruence between their skills and abilities, attitudes and values, and their work-related problems and roles. Likewise, congruence is the degree to which an individual’s personality type and work environment fit (i.e., PE-fit). Congruence is a determinant of positive work-related outcomes such as job satisfaction, stability, and work performance. Holland’s theory of vocational choice is one of the most empirically supported and commonly practiced career theories (Nauta, 2010).

Consequently, Le, Robbins, and Westrick (2014) utilized a PE-fit model to predict undergraduate students’ choice in major and persistence in STEM. Additionally, they
hypothesized that ability (i.e., ACT scores) would also predict students’ major choice and persistence in STEM. Their study included 207,093 undergraduate students entering college. First, they examined the likelihood of enrolling in a STEM major by calculating an Interest-fit Coefficient based on Holland’s codes; this coefficient was then included in the predictive model. The results of their multilevel multinomial logistic regression analysis indicated that students with a higher standardized interest-fit coefficient were significantly more likely to choose a STEM science \((OR = 2.47, \text{partial } R^2 = .06)\) or a STEM quantitative major \((OR = 1.58, R^2 = .03)\). Furthermore, students with a higher standardized interest-fit coefficient were significantly less likely to change to a non-STEM major \((OR = .88, \text{partial } R^2 = -.02)\). These findings provided support for utilizing Holland’s Theory of Vocational Choice in post-secondary STEM populations because PE-fit (i.e., the interest-fit coefficient calculated using Holland’s codes) related to increased odds of choosing STEM majors and persisting in STEM majors. Although this study provided empirical support for utilizing Holland’s Theory of Vocational Choice to understand STEM persistence and major choice, their study had several limitations. First, the small effect sizes for each of the models makes it hard to determine the practical implications of the study. In addition, aggregating various STEM majors into STEM science and STEM quantitative categories reduces the nuances among specific STEM majors. Lastly, using ACT scores to define ability provides a limited definition of students’ ability to thrive in post-secondary STEM coursework.

**Super’s Life-Span Life-Space Theory**

Divergent from Holland’s emphasis on PE-fit, Super (1953, 1990) theorized stages to career development in his Life-Span Life-Space theory. Super recognized the contribution of the PE-fit model in helping people choose careers that matched their skills and abilities; however, he viewed career development as a lifelong process with a series of stages and he viewed career
selection as a culmination of a career-related decisions (Super, 1990). Thus, Super’s Life-Span Life-Space theory includes five stages of career development: growth, exploration, establishment, maintenance, and disengagement (Super, 1990).

The first stage of Super’s (1990) theory, the growth stage, occurs from childhood to adolescence and is a time when children begin to understand the world of work through socializing during play and school. In this first stage children begin to develop their interests and become curious about their future at work. The second stage, the exploration stage, is from late adolescence through emerging adulthood and is a period when individuals begin to narrow their career interests and make occupational choices. The exploration stage is characterized by the formation of a career preference and a tentative plan on how to implement their career preference. Next, is the establishment stage, which is during middle adulthood. During the establishment stage, individuals have chosen a career and gained experience in their work position. The establishment stage is a time when individuals seek to further advance in their career and aim for new levels of responsibility. The last two stages, maintenance and disengagement, take place in late adulthood. Respectively, the maintenance and disengagement stages are a time when people aim to maintain what they have achieved and then transition out of the workforce. Furthermore, Super noted that the process of these stages is not linear but cyclical, in that an individual may cycle through an earlier stage when they experience a career change.

Super’s theory also inspired the development of career assessments such as the Career Development Inventory (CDI; Super, Thompson, Jordan, Lindeman, & Myers, 1981). The CDI which measures a person’s readiness to make educational and career decisions is commonly used with college student populations (Savickas, & Hartung, 1996; Super, Thompson, Jordan, Lindeman, & Myers, 1981). Although there are currently no articles that utilize Super’s theory
to understand STEM attrition/retention or career development in post-secondary STEM populations, one study that is somewhat related to this dissertation utilized a variation of the CDI (i.e., the medical career development inventory [MCDI]) with undergraduate and post-graduate pre-medical students (Henry, Bardo, & Henry, 1992). The MCDI measures an individual’s career development and readiness to cope with the career-related tasks associated with the career of a physician (Savickas, Super, & Thompson, 1983).

In Henry, Bardo, and Henry’s (1992) study, 61 African-American undergraduate and postgraduate pre-medical students participated in career planning seminars. These seminars included an orientation seminar, medical seminar, and a clinical experience (Henry, Bardo, & Henry, 1992). The students were given pre- and posttests of the MCDI at the beginning and end of the career development courses (Henry, Bardo, & Henry, 1992). The results of the ANOVA analysis indicated that the pre-medical students had significantly, positively changed in their career readiness after taking the career seminar courses (Henry, Bardo, & Henry, 1992). Although, Henry, Bardo, and Henry’s (1992) study provided support for utilizing measures related to Super’s theory in post-secondary career courses, this study lacked a control group, had a small sample size, and is now more than ten years old with no follow-up studies.

**Cognitive Information Processing Theory of Career Decision-Making.** After the work of both Holland and Super, more recent career theories such as the Cognitive Information Processing (CIP) Theory of Career Decision-Making, emerged in the literature. CIP focuses on three domains of career development: knowledge, decision-making, and executive processing (Peterson, Sampson, & Reardon, 1991; Peterson, Sampson, Reardon, & Lenz, 2002). The knowledge domain, is comprised of an individual’s acquisition of self-knowledge and occupational-knowledge. Self-knowledge emphasizes the importance of understanding that
perceptions are influenced by past experiences and impact present feelings. Furthermore, occupational knowledge is an individual’s understanding of labor markets, varying occupations, and the skills needed for particular occupations. In addition, the decision-making domain, is the process of CIP and is defined by an individual’s development of the five information-processing skills. These information-processing skills, commonly referred to as CASVE, are critical to making career-related decisions, and include: communication, analysis, synthesis, valuing, and executing skills. Lastly, the executive processing domain, refers to the meta-cognitions related to one’s career decisions. Meta-cognitions can include both positive and negative self-talk around one’s thoughts on their career decisions.

Related to STEM, the aforementioned work of Prescod et al. (2018) and Belser et al. (2017) was grounded in CIP theory. The CTI measures CIP-related constructs in its subscales of: decision making confusion, commitment anxiety, and external conflict (Sampson, Peterson, Lenz, Reardon, & Saunders, 1996). In a recent study, Belser, Shillingford, Daire, Prescod, and Dagley (2018) analyzed data from a multi-year STEM recruitment grant. As part of this grant, 1st year undergraduate students who had not initially declared a major in STEM completed a STEM-focused career planning class. While 1st year students who had initially a declared STEM major completed a STEM seminar class. The 2nd year retention data for students who participated in the grant in their 1st year were: \((n = 270)\) total undergraduate students, \((n = 137, 50.7\%)\) initially undeclared STEM major students retained after taking the STEM career planning course, and \((n = 133, 49.3\%)\) initially declared STEM majors retained after taking the STEM seminar course. The 3rd year retention data for students who participated in the grant in their 1st year were: \((n = 129)\) total undergraduate students, \((n = 76, 58.9\%)\) initially undeclared STEM major students retained after taking the STEM career planning course, and \((n = 53, 41.1\%)\) initially declared STEM majors retained after taking the STEM seminar course.
Belser and colleagues (2018) hypothesized that 1) undergraduate first-to-second year retention in STEM majors can be predicted by ethnicity, gender, initial major, math placement-algebra scores, SAT math scores, participation in a STEM career planning or seminar course, and change in CTI scores and 2) undergraduate first-to-third year retention in STEM majors can be predicted by ethnicity, gender, initial major, math placement-algebra scores, SAT math scores, participation in a STEM career planning or seminar course, and change in CTI scores. The results of the logistic regression analysis suggested that student’s initial major was the most significant predictor of 2nd year retention. Thus, students who initially declared a STEM major were 1.51 times more likely to be retained in their 2nd year when compared to those who were initially undeclared. The odds of being retained in the 2nd year were .14 lower for students who initially did not declare a STEM major. This translates into a 2nd year retention ratio of 50.7% compared to 49.3% for the undeclared student group. Additionally, participating in a STEM course was another significant predictor of 2nd year retention. Students who were undeclared STEM majors during their first year were 2.34 times more likely to be retained in their 2nd year after completing a STEM seminar course. Furthermore, change in CTI score was statistically significant; therefore, the larger the decrease in CTI scores from pre- to posttest, the odds of being retained in the 2nd year increased by 1.02. Moreover, when compared with White students, Asian/Pacific Islander students were more likely to be retained in their 2nd year. In the 2nd year retention model, SAT math scores and math placement-algebra scores were not predictive of retention.

In order to understand 1st year to 3rd year retention, Belser et al. (2018) examined whether the study’s independent variables (i.e., ethnicity, gender, initial major, math placement-algebra scores, SAT math scores, participation in a STEM career planning or seminar course, and change in CTI scores) could predict retention from 1st year to 3rd year. Again, initial major was the most
significant predictor in the model with students who initially declared STEM majors being 1.25 times more likely to be retained in year three when compared to those who were initially undeclared. This translates into a year three retention ratio of 76% compared to 53% for the undeclared student group. Unlike the first model, math placement-algebra scores were a significant predictor of year three retention. Thus, the higher students scored on the math placement-algebra exam, the higher their odds were of being retained in their STEM major during their third year. Students’ math placement-algebra scores were predictive of students’ longer-term retention. Furthermore, although in the first model participation in a STEM seminar course was significant, in the year three retention model, the STEM seminar course was not a significant predictor. Similarly, ethnicity was not a significant predictor of year three retention. In sum, Belser et al.’s (2018) study showed that for students who come into college with an initially declared STEM major, taking a STEM career planning course was associated with increased odds of staying in their major for multiple years. Additionally, participation in a STEM career planning course or STEM seminar course was associated with decreases in students’ negative career thoughts and this decrease in negative career thoughts was associated with increased odd of 2nd year retention. However, initially declaring a STEM major is the most significant predictor of long-term retention and year three retention rates for these students may be harder to associate with completing a STEM career planning courses relate to career development factors such as negative career thoughts and impact undergraduate students’ major retention. However, there is a need to further explore the various ways in which STEM career planning courses relate to career development outcomes. For example, the relationship that participating in a STEM career planning courses has with influencing undergraduate students’ career-related self-efficacy has not yet been examined. Related, SCCT is a more recent theory that expands on Bandura’s (1977) SCT to explain the role of self-efficacy and contextual factors
in forming one’s career interests, goals, and outcome expectations (Lent, Brown, & Hackett, 1994). First, in order to fully explain SCCT, this literature review discusses the conceptualization of self-efficacy described in SCT.

**Social Cognitive Theory.** SCT proposes that individuals are shaped by their environment through the processes of observational learning, modeling, and the influence of self-efficacy (Bandura, 1977). Also, Bandura (2001) emphasizes the importance of human agency in building self-efficacy. Human agency involves constant self-examination, envisioning future events as a result of one’s prior planning, purposefully carrying out plans, and monitoring goal achievement. According to Bandura (1994), self-efficacy is one’s belief in their ability to influence and control the events that happen in their life. Related, Bandura (2008) proposes four ways of building self-efficacy: mastery experience, vicarious learning, verbal persuasion, and psychological arousal. Mastery experiences refers to experiencing tasks first-hand and it is through first-hand experience of accomplishing a challenge that one builds self-efficacy. Moreover, vicarious learning helps an individual build self-efficacy through seeing people similar to oneself and/or seeing role models show consistent effort towards accomplishing a goal. Next, verbal persuasion is the encouragement of others who believe in a person’s abilities and success. Through the influence of other people, verbal persuasion can help build self-efficacy by helping an individual believe that they are capable of reaching their goals. Lastly, physiological arousal is how one’s emotions, mood, and psychical state influence self-efficacy. For example, high levels of stress and anxiety negatively impact a person’s self-efficacy and ability to set and accomplish goals (Bandura, 1986). Moreover, self-efficacy affects one’s perception of external demands and mediates the relationship between external stressors and psychological stress (Bandura, 1995).

Bandura suggested that “scales of perceived self-efficacy must be tailored to the particular domain of functioning that is the object of interest” (Bandura, 2006, p. 307-308).
Related to career development, SCT inspired the development of scales which measure career-related self-efficacy. For example, the Career Decision-Making Self-Efficacy Scale (CDMSE) was developed by Betz and Taylor (1983) and measures an individual's belief that they can successfully complete the tasks that are necessary to making significant career decisions. Likewise, the Career Search Self-Efficacy Scale (CSES) measures a persons’ belief in their ability to perform career selection and job search tasks (Solberg et al., 1994).

*Social Cognitive Career Theory.* Lent et.al. (1994) further explained the role of self-efficacy and contextual influences during career development in their explanation of SCCT. Likewise, SCCT explains three interrelated concepts of career development: how academic and career interests develop, how educational and career choices are made, and how academic and career success is obtained. These interrelated concepts are formed through a cyclical process involving the interests, abilities, values, and environmental factors that impact an individual’s career development (See Figure 1).

*Figure 1.* Social Cognitive Career Theory. This figure demonstrates SCCT constructs. Reprinted from the Journal of Vocational Behavior, 45(1), Lent, Brown, & Hackett, Toward a unifying social cognitive theory of career and academic interest, choice, and performance., 79-122, Copyright 1993, with permission from Elsevier.
Additionally, Brown and Lent (1996) explained that there are three main tenets of SCCT: 1) career and academic interests develop from self-efficacy beliefs and outcome expectations, 2) an individual’s perception of barriers moderates the relationship between interests and career choices, and 3) self-efficacy and outcome expectations develop primarily from performance accomplishments (i.e., individuals benefit from experiences related to their interests). Similar to Holland’s Theory of Vocational Choice (1973), Super’s Life-Span Life-Space Theory (1990), and the CIP Theory of Career Decision-Making (Peterson, Sampson, & Reardon, 1991; Peterson, Sampson, Reardon, & Lenz, 2002), SCCT is aimed at helping individuals choose a career (Brown & Lent, 1996). However, SCCT emphasizes giving individuals access to the broadest array of career choices in order to empower clients to consider career choices that they may have eliminated based on “faulty self-efficacy perceptions, inaccurate outcome expectations,” and sometimes both (Brown & Lent, 1996, p. 357). Furthermore, SCCT is fundamentally a career constructivist theory in that individuals construct their career choice by making meaning from their work-related experiences and future aspirations (Lent, 2005).

SCCT consists of three models: the interest model, the choice model, and the performance model (Lent, 2005). The interest model demonstrates that interest in a career is molded by self-efficacy and outcome expectations for different tasks associated with one’s career choice. Interest is likely to grow once an individual a) views themselves as competent in completing activities (i.e., self-efficacy) and b) anticipates performing the activities will produce positive outcomes (i.e., outcome expectations). Once interests emerge, along with self-efficacy and outcome expectations, goals are formed to sustain an individuals’ engagement in specific career or academic activities. Then, practice towards meeting one’s goals leads to specific performance attainments which feed into self-efficacy and outcome expectations, causing a feedback loop.
Next in the choice model, choosing a career path is not a static act. Thus, once initial career choices are made, they are subject to revision. The career choice process is broken up into three processes: 1) the expression of a goal to enter a specific field, 2) an individual takes action to implement their goal, and 3) performance experiences shape the feedback loop that shapes an individuals’ career choice. Goals motivate individuals’ choice actions and individuals make efforts to achieve their goals (e.g., choosing an undergraduate major in computer science to become a software developer). Furthermore, contextual factors such as culture and gender socialization impact individuals’ self-efficacy, outcome expectations, action towards goals, and career choices.

Lastly, the performance model explains factors that impact individual’s academic and career performance. Performance attainments relate to individuals educational and work success, proficiency, and the degree to which they persist at their choice paths when they come across obstacles. Persistence is related to career decidedness or the stability of one’s career choice. Furthermore, ability (i.e., indicators of achievement, aptitude, or past performance) impacts performance attainments by building domain knowledge and serving as a form of self-efficacy and outcome expectations. Likewise, self-efficacy and outcome expectations influence the performance goals that individuals make for themselves. Figure 2 shows a concept map of SCCT constructs and the study’s variables.
Though SCCT is a newer career development theory, it has been empirically supported in a variety of populations, including STEM post-secondary populations. For example, Lent, Sheu, Singley, Schmidt, Schmidt, and Gloster (2008) used SCCT to investigate how in a semester long undergraduate introductory engineering course, self-efficacy impacts career goals, interests, and the outcome expectations of undergraduate students in STEM majors. Their study included 209 undergraduate engineering students from predominantly white and historically black institutions. The results of their autoregressive path analysis showed some consistency with the SCCT framework. For instance, at time 1 (i.e., the beginning of the semester), self-efficacy yielded significant paths to outcome expectations, interests, and goal persistence at time 2 (i.e., the end of
the semester). This finding was consistent with SCCT which posits that self-efficacy is related to outcome expectations, interest, and goal persistence. However, time 1 outcome expectations did not yield significant paths to interests or goals at time 2 and the time 1 interest path to goals at time 2, was not significant. Consequently, these findings were not aligned with the tenets of SCCT. Though the longitudinal design of this study did explain the temporal nature of self-efficacy and the results provided some support for self-efficacy-based interventions to help with student’s development of major choice and career options, some of the findings were conflicting in regards to SCCT tenets. Thus, there were some limitations to the study. First, the study had a fairly high attrition rate (~44%) which limited the sample size. Additionally, only two time points were observed, a third time point, during the next semester, could have furtherer helped in understanding these constructs across time.

The results of Lent, Lopez, Lopez, and Sheu’s (2008) study, provided more concrete support for the utility of SCCT in understanding STEM populations. The researchers analyzed data from 1208 students majoring in computer disciplines at both predominantly white institutions and historically black colleges and universities (HBCU). Participants completed measures of self-efficacy, outcome expectations, interests, social support and barriers, and educational goals. The pathway from self-efficacy to outcome expectations yielded a statistically significant path ($\beta = .71$). In addition, self-efficacy yielded statically significant paths to interests ($\beta = .61$), major choice ($\beta = .30$), and social supports ($\beta = .64$). Although, outcome expectations did not yield significant paths to interests or goals, the model fit generally well with SCCT and the large effect sizes show the practical implications of using SCCT to understand the educational goals of undergraduates in computing disciplines. However, this study has limited
generalizability to other STEM fields because the study only included undergraduate students majoring in computer disciplines.

Because of the gender and racial disparities regarding with post-secondary STEM retention, Lent and colleagues (2013) sought to assess the model fit of SCCT constructs with engineering undergraduate students based on demographic predictors (i.e., gender and race). Thus, with 1,377 undergraduate engineering students across two universities (i.e., one PWI and one HBCU), they examined the interplay of educational/vocational satisfaction, interest, choice, and intentions to remain in engineering major (i.e., performance/persistence) in women, men, and racial subgroups of students. The study included \( n = 456 \) women and \( n = 918 \) men. Additionally, the sample consisted of mostly White students (58%) and Asian students (20%), with Black (15%) and Hispanic (4%) students making up the remainder of participants that reported their race. The results of the persistence pathway in the structural equation model for in the women subgroup were significant and accounted for large amounts of variance \( (R^2 = .56) \). In men subgroup, the results of the persistence were also significant and accounted for relatively large amounts of variance \( (R^2 = .39) \). Furthermore, the persistence pathway was significant and accounted for large amounts of variance for majority students \( (R^2 = .47) \) and minority students \( (R^2 = .43) \). Thus, men and women, as well as racial minorities, who had strong self-efficacy, interests, outcome expectations, and academic satisfaction were more likely to persist in their engineering majors. Although, this study added to the literature examining demographic characteristics in regards to STEM persistence, this study was cross-sectional; therefore, casual inferences could not be made. In addition, grouping all minority groups together in STEM persistence literature is misleading because Asian populations are not an underrepresented racial group in STEM disciplines (NCES, 2017).
More recently, Lent, Miller, Smith, Watford, Lim, and Hui (2016) tested SCCT with 908 undergraduate engineering students from two universities in the Mid-Atlantic region. They examined student’s self-efficacy, outcome expectations, environmental support, interest, academic satisfaction, persistence goals, trait positive affect, and behavioral persistence during the last three weeks of students’ first (i.e., time 1) and second (i.e., time 2) semesters. The results of their autoregressive path analysis showed that intended persistence ($\beta = .29$) had the strongest direct pathway to academic persistence. Additionally, social support had an indirect relationship to persistence through satisfaction, math SAT scores were indirectly related to persistence through self-efficacy, and math SAT scores were indirectly linked to satisfaction through self-efficacy. These reciprocal pathways were consistent with SCCT and highlight the predictive nature of SCCT in explaining persistence in STEM fields. However, this study only included engineering majors and due to the lack of data collection on students’ GPAs, this study did not include an accurate view of students’ current academic performance in STEM.

**Gaps in the Literature on Study Variables**

Post-secondary career development interventions and initiatives are intended to help students navigate the tasks and skills associated with career readiness and decision-making (Maietta, 2013). Career development interventions provide students with tasks and skills related to: value clarification, goal setting, identifying and seeking career alternatives, anticipating future events, and gathering occupational information (Mitchell & Krumboltz, 1996). From a SCCT perspective, self-efficacy plays a salient role in harnessing students’ ability to participate in, and complete career development and career decision-making tasks (Lent, 2005). Gottfredson (1996) suggested that students’ faulty self-efficacy beliefs and outcome expectations can lead to career indecision. Career coursework is one career development intervention that offers undergraduate students with in-depth opportunities to enhance their career development (Maietta, 2013). Thus,
it is important to consider the role of career planning coursework in increasing students’ career-related self-efficacy. In regards to career search self-efficacy, prior research has suggested that CSES may be improved through participation in career planning courses (McWhirter, Rasheed, & Crothers, 2000).

**Career Search Self-Efficacy**

Maitta’s (2013) study examined the relationship between the degree of participation in a career planning course and CSES. The study included 242 undergraduate students who participated in a one-credit-hour career course focused on helping students to complete various career related tasks including: developing individual portfolios, exploring employment options, creating professional documents (i.e., resumes and cover letters), job searching, practicing interviewing, understanding networking, and attending various workshops. Students assessed their own levels of participation and class attendance and completed the CSES. Bivariate correlations showed that CSES positively correlated with students’: frequency of participation in class discussions \(r = .51\), attendance \(r = .23\), group participation \(r = .40\), completion of course assignments \(r = .37\), and overall career program engagement \(r = .40\). The results of the regression analysis indicated that frequency \(\beta = .40\) and group participation \(\beta = .23\) were significant, positive predictors of CSES. Thus, the more students attended the career planning class and participated in the class, the higher their CSES scores.

Although Miatta’s (2013) study explored the relationship between participating in a career planning course and CSES, this study had a cross-sectional design. Thus, the temporal nature of CSES during a career planning course was not explored and causation could not be determined. In addition, this study did not focus on students in STEM majors and career planning courses that are specifically designed to help students remain in STEM majors and
transition to STEM careers. To date, no study has explored the CSES of undergraduate students in a STEM planning course.

**The need for literature on stress and self-efficacy in STEM undergraduate students.**

Zajacova, Lynch, and Espenshade (2005) investigated the joint effects of academic self-efficacy and stress on the academic performance of 107 minority freshman at an urban university. They developed a structural equation model that explained the importance of stress and self-efficacy in predicting first-year GPA, number of accumulated college credits, and college retention after the first year. The researchers hypothesized that stress would have a negative relationship with measures of academic success and self-efficacy would be associated with positive outcomes for academic success. The results indicated that self-efficacy was a strong predictor of academic success while stress had a negative influence on GPA and staying enrolled in college. However, the results suggested that stress had a negative but statistically insignificant relationship with GPA. Surprisingly, stress had a marginally positive relationship with enrollment at the start of the second year. The researchers hypothesized that this finding might be due to their lack of distinction between stress due to experiencing a challenge and stress due to psychological threat. Thus, Zajacova et al. (2005) suggested that future studies should look more closely at stress related to challenge appraisal and threat when predicting academic outcomes for students. This study highlights the need for more understanding regarding the relationships between both psychological stress and self-efficacy. Furthermore, this study only focused on academic outcomes; however, there is a need to explore the relationships between stress and career outcomes, especially for students pursuing STEM majors.

Related, Baghurst and Kelley (2014) looked at changes to 531 college students’ cognitive-behavioral stress management after receiving stress interventions during a semester of
a course. Their study had only a treatment group and no control. The course met three days a week for 50 minutes. Students in the stress management group received lectures; cognitive–behavioral exercises; mental and physical relaxation strategies and practice; and exercise and wellness participation. In addition, each student was given a workbook titled “Exploring Your Stress: An Introductory Program” which was designed specifically for the study. Moreover, students in the physical activity group received lectures; however, most of the time was spent participating in activities such as basketball or volleyball. Further, students in the cardiovascular group also received lectures and activities such as aerobics. Students in each group received pre- and post-tests of perceived stress, test anxiety, and personal burnout measures. The researchers predicted that stress levels for perceived stress, test anxiety, and burnout would show the greatest reduction over the semester for students in the stress management groups. Interestingly, students in both the stress management and physical activity group showed the greatest reduction in perceived stress, test anxiety, and personal burnout of the course of the semester. Their results indicated that college students stress can change over time and courses that provide stress reduction interventions can reduce college students’ stress. Although Baghurst and Kelley (2014) and Zajacova et al.’s (2005) studies were not specific to STEM populations they do show the nuances of college students’ stress overtime and the need for interventions that address college students stress.

Counselors can play an integral role in developing STEM career initiatives that enhance the career development and address the psychological wellbeing of undergraduates pursuing STEM fields. According to the ACA, counselors participate in collaborative approaches that promote the wellness, mental health, and career goals of the people we serve (ACA, 2019). Thus, counselors’ involvement in STEM initiatives can promote a more holistic approach to promoting
STEM careers. Likewise, the work of Prescod et al. (2018) and Belser et al. (2017) highlighted the importance of counselors’ involvement in STEM career coursework in order to help promote student’s career development and retention. However, exploring the influence of stress in order to further enhance the literature on STEM post-secondary career development and retention can help advocate for the role of counselors in addressing the physiological and career-related needs of undergraduates in STEM.

Increases in college student’s life stress are associated with lower levels of career decidedness and satisfaction with career choice (Bullock-Yowell, Peterson, Reardon, Leiecrer, & Reed, 2011). While psychological factors are discussed in relation to STEM persistence, they are poorly understood and limitedly studied (Park, Williams, Hernandez, Agocha, Carney, DePetris, & Lee, 2019). Stress can overwhelm and dysregulate biological systems (Amirkhan, 2018). In terms of psychological systems, individuals experience stress when environmental demands exceed their personal resources (Lazarus & Folkman, 1984). Furthermore, stress becomes destructive when individuals are exposed to demanding events and have inadequate resources to meet those demands (Cohen, Kamarck, & Mermelstein, 1983). This state is referred to as stress overload (Amirkhan, 2018).

Although stress is not commonly studied in STEM populations, Park et al. (2019) aimed to explore the role of self-regulation (i.e., the degree to which people work towards their desired goals especially under stress) in URM’s STEM persistence. Surprisingly, their study found that only one aspect of self-regulation- alcohol use and the use of other drugs to cope- was a significant, negative predictor of academic persistence (Park, Williams, Hernandez, Agocha, Carney, DePetris, & Lee, 2019). Related, in a qualitative study on self-efficacy among STEM undergraduate students with disabilities, students explained that experiencing high amounts of
stress sometimes hindered their academic performance (Jenson, Petri, Day, Truman, & Duffy, 2011). However, in Perez, Cromely, and Kaplan’s (2014) study on the role of college students’ identity development and motivational beliefs in predicting STEM achievement and persistence, perceiving a STEM major as too stressful and anxiety provoking did not lead to increased likelihood of leaving a STEM major. Likewise, Rice et al. (2015) examined perfectionism and perceived academic stress in a sample of 432 college freshman in STEM majors. Students completed perfectionism scales and measures of perceived academic stress at monthly intervals 3 times in the fall and spring semesters. The latent profile analysis revealed that students fell into low, medium, and high stress groups and students who fell into with a maladaptive perfectionism personality type were likely to have low stress patterns over the course of the semester. Moreover, those who exhibited adaptive perfectionism were more likely to transition from moderate stress to low stress over the course of a semester. In addition, women were more likely to be maladaptive perfectionists and were more likely to be in either the high stress or moderate stress groups. While perceived stress has been studied with students in STEM majors over the course of a semester, there is a dearth in the literature regarding the role of perceived stress during a STEM career planning course. In sum, there is limited and conflicting literature surrounding the influence of stress in STEM populations.

Despite the current support for SSCT in the STEM literature, there is a need to further explore SCCT in relation to STEM initiatives, specifically STEM career planning courses, and understand the role of stress plays in developing career self-efficacy. None of the previously described studies that utilized SCCT in STEM populations included an intervention aimed at increasing STEM undergraduates’ career-related self-efficacy (Lent et al., 2008; Lent et al., 2013; Lent et al, 2016; Lent, Lopez, Lopez, & Sheu, 2008). Furthermore, the literature that
explores the career-related self-efficacy of undergraduate students in career planning courses does not emphasize STEM-focused career planning courses. Instead of focusing on career self-efficacy, the literature that focuses on career development in STEM career planning courses studied decreases in negative career thoughts (Belser et al., 2017; Belser et al., 2018; Prescod et al., 2018). Therefore, the purpose of this proposed study was to 1) contribute to the literature on SCCT based interventions for undergraduates pursuing STEM fields by discussing the influence of a career planning course on students’ CSES, 2) explore the temporal relationships between stress and CSES, and 3) relate CSES and STEM career planning courses to STEM major retention in a diverse population of undergraduates majoring in engineering.

**Operational Definitions of Variables**

The following section will include a description of the terms that are referenced throughout this dissertation:

**VCU-COE Professional Development**- The 1-credit hour, STEM career planning and professional development course used in this study to aid undergraduate engineering students in their career goals and development. This course enhances student’s career development by requiring students to engage with Engineering Career Services, gain exposure to STEM employers; participate in career-related tasks such as making resumes, developing a career plan, and setting career goals.

**Career development**- The process of engaging in career planning, career decision-making, and career exploration.

**Career Self-Efficacy**- The degree to which one believes in their ability to engage in career-related tasks. This will be measured using the Career Search Self-Efficacy Scale (CSES; Solberg et al., 1994).
**Perceived Stress**: Stress is the primary appraisal process of coping and is one’s subjective evaluation of an experience as being beyond their ability to respond to a situation effectively (Cohen, Kamarck, & Meruelstein, 1983; Lazarus & Folkman, 1984). Stress will be measured using the Personal Vulnerability subscale of the Stress Overload Scale- Short Form (SOS-S; Amirkhan, 2018).

**Retention**: In this study retention refers to undergraduate engineering students registering for classes in the semester that follows their participation in the VCU-COE Professional Development course.

**STEM Career Planning Course**: STEM career planning course refers to undergraduate coursework related to career development and is specifically focused on STEM disciplines.

**STEM Initiatives**: Career and academic interventions aimed at reducing disparities in the STEM workforce by promoting interest and persistence in STEM.
Chapter Three
Methodology

Design

This study utilized a repeated measures quasi-experimental, quantitative single group pre, mid-, and post-test design to examine differences in the study’s variables overtime. This study used secondary data gathered from a STEM Career Planning Course over the course of two semesters. The research methodology discussed in this chapter includes: participants, instruments, intervention, procedure, data analysis, and limitations. In order to answer research questions one and two, the analysis included a repeated measures multilevel model (MLM) and to the answer the third and final research question, a logistic regression was used. Below are the research questions and hypotheses answered in this study:

RQ1: Over the course of a semester in a STEM career planning course, is there a change in scores on career search self-efficacy?

\[ H_0: \text{There will be no change in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy.} \]

\[ H_a: \text{There will be at least a change in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy.} \]

RQ2: Will early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy vary based on undergraduate engineering students’ perceived stress?
$H_0$: There will be no differences between in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy based on undergraduate engineering students’ perceived stress.

$H_a$: There will be differences between in early (week 1), mid (week 6), and end-of-semester (week 14) on career search self-efficacy based on undergraduate engineering students’ perceived stress.

$H_b$: There will be significant decreases in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy based on undergraduate engineering students’ perceived stress.

$H_c$: Decreases in early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy will vary over time depending on undergraduate engineering students’ perceived stress.

RQ3: Do undergraduate engineering students’ career search self-efficacy scores predict students’ odd of persisting in their major for the following semester?

$H_0$: Career search self-efficacy scores will not significantly predict students’ odd of persisting in their major for the following semester.

$H_a$: Career search self-efficacy scores will significantly predict students’ odd of persisting in their major for the following semester.

$H_b$: Higher career search self-efficacy scores will increase students’ odd of persisting in their major for the following semester.
An *a priori* power analysis using Stata 14 (StataCorp, 2015) and G*Power 3 (Faul, Erdfelder, Lang, & Buchner, 2007) software was conducted to determine if the anticipated sample size will provide sufficient power for data analysis. First, to determine the adequate sample size needed to answer research RQ1 and RQ2, the `ipdpower` command in Stata was used to conduct simulations that calculate power for mixed effects two-level data structures (Kontopantelis, Springate, Parisi, & Reeves, 2016). Using the code `ipdpower, sn(100) ssl(750) ssh(250) b0(0) b1(.5) b2(-.3) b3(-.3) minsh(3) cexp`, the simulations revealed a sample size of 250 participants would fully power a repeated measures MLM with medium effect sizes and interaction effects (See Appendix A). In the aforementioned code: `sn` refers to the number of simulations executed; `ssl` is the total number of clusters at each time point (i.e., 250 x 3); `ssh` is the estimation of number of participants; `b0` is the coefficient for the intercept; `b1` is the coefficient for CSES score over time; `b2` is the coefficient for the covariate (i.e., stress); `b3` is the coefficient for the covariate interaction (i.e., the interaction between stress and time); `minsh` is the number of time points; and `cexp` indicates that the outcome variable is continuous (i.e., CSES).

Next, to determine the sample size needed to answer RQ3, an *a priori* power analysis was done using G*Power 3 software (Faul, Erdfelder, Lang, & Buchner, 2007). The persistence question was only be answered by participants who took VCU-COE Professional Development in Fall 2019 semester. The power analysis was conducted with .80 power, an alpha set to .05, and a medium (.5) effect size and revealed that 95 participants was sufficient.

**Participants**

Participants included *N = 286* undergraduate engineering students in a VCU-COE Professional Development course. Participants in this study completed the surveys as a class assignment in the Fall 2019 and Spring 2019 semesters. All participants were at least 18 years
The mean age of participants in this sample was 20.71 years old, $SD = 4.01$. Week 1 of the Fall 2019 and Spring 2019 cohorts of the intervention included: $n = 19$ Asian, $n = 16$ Black, $n = 74$ White, and $n = 15$ participants who identified as other than the race options given ($n = 162$ participants did not respond to the race item). At week 6, the sample included $n = 16$ Asian, $n = 15$ Black, $n = 73$ White, and $n = 17$ participants who identified as other than the race options given, ($n = 163$ participants did not respond to the race item). Lastly, at week 14, the Fall 2019 and Spring 2019 cohorts included $n = 38$ Asian, $n = 26$ Black, $n = 114$ White, and $n = 28$ participants who identified as other than the race options given, ($n = 75$ participants did not respond to the race item).

Further, at week 1; week 6; and week 14; respectively, $n = 13; n = 14; and n = 20$ participants identified as Hispanic/Latino. In addition, at week 1; week 6; and week 14; respectively, $n = 57; n = 52; and n = 43$ participants identified as first-generation college students. Moreover, at week 1, this study included participants majoring in: $n = 15$ biomedical engineering, $n = 14$ chemical engineering, $n = 4$ computer engineering, $n = 1$ computer science, $n = 3$ electrical engineering, and $n = 87$ mechanical engineering ($n = 162$ did not disclose their engineering major at week 1). At week 6, this study included participants majoring in: $n = 15$ biomedical engineering, $n = 14$ chemical engineering, $n = 4$ computer engineering, $n = 2$ computer science, $n = 2$ electrical engineering, and $n = 83$ mechanical engineering ($n = 164$ did not disclose their engineering major at week 6). At week 14, this study included participants majoring in: $n = 39$ biomedical engineering, $n = 37$ chemical engineering, $n = 4$ computer engineering, $n = 1$ computer science, $n = 4$ electrical engineering, and $n = 90$ mechanical engineering ($n = 175$ did not disclose their engineering major at week 14).

Additionally, at week 1; week 6; and week 14; respectively, this study included: $n = 4$ freshman, $n = 64$ sophomores, $n = 42$ juniors, and $n = 13$ seniors ($n = 124$ participants did not
disclose their classification at week 1); \( n = 4 \) freshmen, \( n = 62 \) sophomores, \( n = 40 \) juniors, and \( n = 15 \) seniors (\( n = 121 \) participants did not disclose their classification at week 6); and \( n = 62 \) freshman, \( n = 73 \) sophomores, \( n = 51 \) juniors, and \( n = 20 \) seniors (\( n = 75 \) participants did not disclose their classification at week 14). Moreover, at week 1; week 6; and week 14; respectively, this study included: \( n = 80 \) female students, \( n = 161 \) male students, and \( n = 45 \) participants who did not disclose their gender or identified as other; \( n = 71 \) female students, \( n = 139 \) male students and \( n = 74 \) participants who did not disclose their gender or identified as other; and \( n = 65 \) female students, \( n = 120 \) male students, and \( n = 95 \) participants who did not disclose their gender or identified as other.

As part of the intervention, participants completed career advising and mock interview appointments with career counselors. Participants rated how helpful each appointment was at each timepoint (“1- not helpful at all, 3- neutral, 5- extremely helpful”). Only \( n = 2 \) participants completed their mock interview appointment at week one (\( m = 3.00, sd = 1.14 \)). At week 6, \( n = 74 \) participants completed their mock interview appointment (\( m = 3.45, sd = .71 \)). At week 14, \( n = 176 \) participants completed their mock interview appointment (\( m = 3.56, sd = .75 \)).

Regarding the career advising appointments, \( n = 12 \) participants completed their career advising appointment at week one (\( m = 3.25, sd = .62 \)). At week 6, \( n = 84 \) participants completed their career advising appointment (\( m = 3.21, sd = .76 \)). Finally, at week 14, \( n = 171 \) participants completed their career advising appointment (\( m = 3.25, sd = .73 \)).

**Instruments**

The dataset used for the current study included demographic questions, the CSES scale, and the brief version of the Stress Overload Scale’s (SOS-10) Personal Vulnerability (PV) subscale. The participants completed the survey at three timepoints throughout the semester.
resulting in early (week 1), mid (week 6), and end-of-semester (week 14) tests of the study’s variables.

**Demographics Questionnaire.** The early (week 1), mid (week 6), and end-of-semester (week 14) tests included demographic questions regarding first-generation status, race, gender, year in school, major, and eligibility to work in the U.S. In addition, participants were asked whether they have completed the required mock interview and career advising appointments and to rate how helpful their appointments were on a scale from (“1- not helpful at all, 3- neutral, 5- extremely helpful”). Furthermore, participants were asked to rate their confidence in their career choice and how confident they are that they complete their degree in engineering (“1- not confident at all, 5- extremely confident”). Participants were asked if they plan on enrolling in engineering courses for the following semester (“5- extremely likely, 3- somewhat likely, 1- not likely at all”).

**Career Search Self-Efficacy (CSES; Solberg et al., 1994).** The CSES scale is a 35-item Likert-type scale instrument that asks participants to rate on a scale of (“0-very little”) to (“9-very much”), how confident they are in their ability to complete career-related tasks such as “identify and evaluate your career goals”, “conduct an information interview,” “market your skills and abilities to an employer,” etc. The CSES scale measures a person’s belief in their ability to participate in career selection and search using four subscales: networking efficacy, job search efficacy, personal exploration efficacy, and interviewing efficacy. Convergent validity was supported by the CSES’s association with the CDMSE scale while discriminate validity was established by exploring the CSES’s relationship with measures of human agency, assertiveness, and personality. In Solberg et al.’s (1994) study with university students from the Midwest the Cronbach’s coefficients alpha was .97 for the full scale, .95 (job search efficacy), .91(interviewing efficacy), .92 (networking efficacy), and .87 (personal exploration efficacy).
Stress Overload Scale-10 (SOS-10; Amirkhan, 2018). The SOS-10 is a 10 item Likert-type scale measuring event load (EL) stress and personal vulnerability (PV) to stress. The SOS-10 asks participants to rate on a scale (“1= not at all, 5= a lot”) their subjective feelings of stress over the last week. For example, participants rate feeling “inadequate” and “like nothing was going right.” Even numbered items comprise the EL subscale and odd numbers comprise the PV scale. Each subscale typically has high Cronbach’s coefficient alpha ($\alpha = .94$) and the SOS-10 has shown good test-retest reliability. Construct validity was established by comparing the measure to the Perceived Stress Scale and the full 30 item SOS-S.

Intervention

Participants completed the VCU-COE Professional Development class- a STEM Career Planning Course offered by the VCU-COE Career Services department for undergraduate engineering students at the university. The course was 1) offered in the Fall 2019 and Spring 2019 semesters, 2) required for Mechanical Engineering, Biomedical Engineering, and Chemical Engineering majors, and 3) required for all students interested in completing an internship or co-op experience. Additionally, the VCU-COE Professional Development class was a 1 credit-hour graded course that met twice a week for 50 minutes. VCU-COE Professional Development course objectives were intentionally aligned with the Accreditation Board for Engineering and Technology, Inc (ABET) accreditation requirements and course learning outcomes and objectives. According to the course syllabus the course objectives were for students to:

- Gain an understanding of the professional development opportunities and career pathways available to College of Engineering students and graduates
- Develop an understanding of employer expectations for professional and ethical behavior
- Gain an understanding of and prepare for the job search and hiring process
• Develop communication skills necessary for a successful job search and for working in a professional environment

• Develop an understanding of the benefits of networking and life-long learning

Assignments and Timeline

The schedule for the course varied slightly each semester; generally, the beginning of the course (weeks 1-6) was focused on preparing students for the career fair, the middle of the course was dedicated to building students’ interviewing and networking skills (weeks 6-13), and the end of the class was focused on developing a career plan and presenting their career plan with a partner (weeks 13-15). Many of the assignments align with SCT, SCCT, and CSES domains. Table 2 shows an overview of the major assignments in the course and their alignment with SCT, SCCT, and the CSES subscales.

Students engaged in vicarious learning activities each semester prior students who have already gained work experience with engineering employers return to the course to share their experience answer questions. Thus, students in the class learned through others students’ experiences. Additionally, a SCCT-aligned assignment involved students’ development of a list of employers in industries of interest to students. This assignment aimed at helping students refine their career choice. Likewise, completing a career counseling appointment was another SCCT and SCT aligned assignment. Most students met with a counselor education doctoral student, trained in career and mental health counseling to explore their career interests and goals. Additionally, verbal persuasion played a role in these career counseling sessions, in that the counselor drew from students’ strengths to help encourage students to complete career-related tasks. Further, the CSES interviewing self-efficacy domain was closely aligned with several of the course assignments including assignments in which students had to conduct an in-person
mock interview and an online mock interview. In addition, stress was addressed in the class. The counselor education doctoral student guest lectured in the course to discuss stress, wellness, and to help students make plans to help reduce their stress. Students also completed additional career-related tasks such as making a resume and writing a cover letter, attending the VCU-COE career fair, and attending employer guest lectures. Students also had the opportunity to attend professional development opportunities and events hosted by Engineering Career Services for extra credit.

**Procedure**

This section outlines the procedures implemented for data collection. The researcher sought the approval of the VCU Engineering Career Services Director to use the anonymous dataset collected from the professional development course. Then, the researcher informed the Institutional Review Board (IRB) of the study and received notification from the IRB that the study was not considered human subjects research; thus, a full IRB submission was not necessary (See Appendix B). In the Fall and Spring 2019 semesters, one instructor taught four sections of VCU-COE Professional Development. Data were collected at each timepoint (week 1, week 6, and week 14) using Research Electronic Data Capture (REDCap) a secure web-based application designed to support data capture for research studies (Harris, Taylor, Thielke, Payne, Gonzalez, & Conde, 2009). Completing the survey was a class assignment and students indicated under the Blackboard survey assignment that they had completed the survey. The survey took approximately 15-20 minutes to complete at each timepoint.

**Data Analysis**

The procedures for data analysis are as follows. Data were analyzed using Stata 14 (StataCorp, 2015). First, means, standard deviations, and bivariate correlations were calculated for the study’s variables (i.e., demographics, CSES, and PV).
A repeated measures multilevel model (MLM) was used to compare changes in early (week 1), mid (week 6), and end-of-semester (week 14) scores on the CSES scale and to explain the relationship stress had with CSES over time. In the null repeated measures model, the dependent variable was CSES and the independent variable was time or week 1, week 6, and week 14 of the VCU-COE Professional Development class. Additionally, this study sought to explore how stress impacts CSES. Thus, using a hierarchical approach, predictors; covariates; and random slopes and intercepts were added to the MLM. First, students’ scores on the Personal Vulnerability (PV) subscale of the SOS-10 were added to the MLM as a predictor of CSES. Then, the interaction between PV and time (i.e., week 1, week 6, and week 14) was added to the model to explore how the shared variance between perceived stress and time predicts changes in CSES scores. The last step in building the final MLM included testing random slopes for PV and CSES scores. Lastly, a logistic regression was used to investigate the impact of students’ CSES scores on their odds of persisting in an engineering major. The independent variable was CSES scores and the dependent variable was retention as defined by student’s intention to continue in an engineering major the semester after they complete VCU-COE Professional Development.

Since the intervention was a class assignment, missing cases were expected and there were instances in which participants completed one or two iterations of the survey but not all three. Thus, maximum likelihood estimation was used to prepare the dataset for multilevel analysis (Garson, 2019). This was the default setting in Stata.

RQ1: Over the course of a semester in a STEM career planning course, is there a change in scores on career search self-efficacy?

First, to answer RQ1, CSES was added to the model as the dependent variable and time was added as a predictor variable. Then, the ICC was calculated for the null model to ensure that
a repeated measures MLM is appropriate. An ICC of at least .05 would justify the need to use multilevel modeling. To assess model fit, the AIC and BIC were calculated.

**RQ2: Will early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy vary based on undergraduate engineering students’ perceived stress?**

Next, to answer the second research question, PV was added to the model as a predictor. Then, the AIC and BIC calculations were assessed. In order to show improved model fit, the AIC and BIC scores should decrease. Given that the AIC and BIC scores decreased after adding PV as a predictor, a covariate was added to the model as a predictor of CSES. This covariate is the interaction between PV and time (i.e., week 1, week 6, and week 14). Again, the AIC and BIC scores were calculated to ensure that the final model had the best model fit. Following, random intercepts and slopes for CSES scores were tested and the AIC and BIC scores were examined. To compute an effect size for the final model a $R^2$ statistic was calculated in order to explain how much variance the final model explains when compared to the null model estimates. In order to provide a visual representation of the final model estimates, a graph was constructed using the `marginsplot` command in Stata.

The statistical assumptions for MLM include: linear relationships, homoskedasticity, normal distribution of errors, and no outliers or multicollinearity (Garson, 2019). After the final model with the best fit was determined. The residuals of the MLM were examined in order to check the statistical assumptions. Stata allows for the review of standardized conditional residuals. Therefore, the standardized conditional residuals were analyzed using a histogram; boxplot; and residual vs fitted (RVF) plot. Then, the researcher reran the model with robust standard errors using the `vce` command. Next, the researcher reran the model with outliers removed. The results of each model were compared to ensure that the model had not significantly changed and did not violate statistical assumptions.
RQ3: Do undergraduate engineering students’ career search self-efficacy scores predict students’ odds of persisting in their major for the following semester?

Lastly, to answer the third research question, a logistic regression was analyzed. The sample size for the logistic regression was smaller \( N = 100 \) because the categorical item related to students’ plans to continue in an engineering degree for the following semester was only asked to the Fall 2019 cohort. Additionally, the logistic regression only included students’ responses at the final timepoint (week 14). After, analyzing the logistic regression the model was examined to assess the statistical assumptions. The assumptions for a logistic regression are similar to the assumptions for a linear regression and MLM, with the exception that the dependent variable is categorical; thus, the sensitivity and specificity of the model must be evaluated (Acock, 2018).

**Exploratory Model**

As an exploratory analysis, another repeated measures MLM was analyzed. This model included CSES as the dependent variable and examined changes in CSES based on demographic characteristics. Predictors such as race, ethnicity, gender, and first-generation status were added to the model. Also, participants’ ratings of their career advising and mock interviewing appointments were added to the model as predictors of CSES over time.

**Conclusion**

This chapter explained the participants, intervention, instruments, and data analysis that will be utilized in this study. This study adds to the literature regarding STEM career planning courses by introducing a different statistical approach, repeated measures MLM. The previous studies in Chapter Two (i.e., Belser et al., 2017; Belser et al., 2018; Miatta, 2013; Prescod et al., 2018) that were most related to the current investigation utilized repeated measures ANOVA or multiple regression analysis. Thus, the effects of clustering were not explored. Utilizing multilevel modeling to understand the influence of STEM career planning courses, reduces error
by exploring between and within student variance to provide more support for career planning
courses as impactful career development interventions. Further, a multilevel modeling approach
aligned with the theoretical underpinnings of this study because multilevel models allow for the
consideration of context in the statistical analysis. Likewise, SCCT explains the role of
contextual factors in building one’s self-efficacy, career interest, goals, and choice. The results of
the analysis are discussed in Chapter Four.
Chapter Four

Results

The purpose of this study was threefold. The researcher sought to examine: 1) how participating in a STEM career planning course changed students’ CSES over the course of a semester, 2) examine the influence of perceived stress on participants’ CSES scores, and 3) examine the relationship CSES has in predicting participants’ odds of persisting in their major. In Chapter One, the researcher provided an overview of the dissertation study. Chapter Two explained the background literature on the study’s variables, the theoretical underpinnings of the study, and the gaps in the literature which the present study sought to fill. Next, in Chapter Three, the researcher presented the study’s research questions and the rationale for a quantitative design with a repeated measures MLM and logistic regression analysis. In the Chapter Four, the researcher discusses the study’s results.

First, Chapter Four presents a preliminary analysis of the study’s variables including calculations of: the Cronbach’s coefficients alphas of the study’s instruments, means, standard deviations, frequencies, and bivariate correlations of the study’s variables. Next, Chapter Four presents the results of the repeated measures MLM and how the researcher addressed the statistical assumptions. Following, the researcher presents results of the logistic regression analysis. Lastly, the results of the exploratory analysis are reported. These statistical analyses were used to answer the following research questions:
RQ1: Over the course of a semester in a STEM career planning course, is there a change in scores on career search self-efficacy?

RQ2: Will early (week 1), mid (week 6), and end-of-semester (week 14) scores on career search self-efficacy vary based on undergraduate engineering students’ perceived stress?

RQ3: Do undergraduate engineering students’ career search self-efficacy scores predict students’ odd of persisting in their major for the following semester?

**Preliminary Analysis**

Data were collected at three timepoints of the intervention. Participants completed the surveys as a class assignment at week 1, week 6, and week 14 of the Fall and Spring 2019 semesters. Thus, in order to ensure the reliability of the study’s instruments, the Cronbach’s coefficients alphas were calculated at each time point. The results of the reliability analysis in for this specific sample are presented in Table 3.

Table 3

<table>
<thead>
<tr>
<th>Scale</th>
<th>Cronbach's Coefficients Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Week 1</td>
</tr>
<tr>
<td>CSES</td>
<td>.98</td>
</tr>
<tr>
<td>Perceived Stress</td>
<td>.82</td>
</tr>
</tbody>
</table>

Note: CSES = Career Search Self-Efficacy Scale (Solberg et al., 1994), Perceived Stress = Personal Vulnerability Subscale of the Stress Overload Scale Short Form (Amirkhan, 2018)

Next, means and standard deviations for the study’s continuous variables (i.e., CSES and PV) were calculated at each timepoint. The results are presented below in Table 4.
Table 4

Descriptive Statistics

<table>
<thead>
<tr>
<th>Scale</th>
<th>M</th>
<th>SD</th>
<th>M</th>
<th>SD</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Week 1</td>
<td>Week 6</td>
<td>Week 14</td>
<td>Week 1</td>
<td>Week 6</td>
<td>Week 14</td>
</tr>
<tr>
<td>CSES</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>N = 286</td>
<td>N = 284</td>
<td>N = 281</td>
<td>N = 286</td>
<td>N = 284</td>
<td>N = 281</td>
</tr>
<tr>
<td></td>
<td>165.13</td>
<td>166.20</td>
<td>167.33</td>
<td>77.94</td>
<td>101.44</td>
<td>112.80</td>
</tr>
<tr>
<td>Perceived Stress</td>
<td>N = 256</td>
<td>N = 222</td>
<td>N = 203</td>
<td>N = 256</td>
<td>N = 222</td>
<td>N = 203</td>
</tr>
<tr>
<td></td>
<td>10.21</td>
<td>12.09</td>
<td>12.75</td>
<td>4.38</td>
<td>5.05</td>
<td>5.45</td>
</tr>
</tbody>
</table>

Note: CSES = Career Search Self-Efficacy Scale (Solberg et al., 1994), Perceived Stress = Personal Vulnerability Subscale of the Stress Overload Scale Short Form (Amirkhan, 2018)

In order to answer RQ3, a categorical item was used to measure participants’ persistence in their major. This item was asked to the Fall 2019 cohort that completed the intervention. Thus, the sample size was reduced to the N = 147 participants that completed the survey at least once in the Fall 2019 semester. Of the participants who completed the survey at least once in Fall 2019, N = 100 responded to the categorical item related to persistence. Originally, the item regarding persistence in major had five categories and a logistic regression was used to predict missingness for this item based on race, gender, ethnicity, and first-generation status. None of the demographic characteristics were statistically significant predictors of missingness for the persistence item; thus, there were no statistical differences between participants who did and did not respond to the persistence item based on demographic characteristics. Due to low frequencies in some categories, the original five categories were then condensed into two categories - high and low likelihood of persisting in major for the following semester. The histogram of participants’ responses is shown in Figure 3.
Figure 3. Histogram of Persistence Responses. This figure demonstrates the frequency of participants responses to “how likely are you to continue with an engineering degree next semester?”

After, creating a histogram of the categorical variable used in this study (i.e., persistence in major), bivariate correlations of the study’s continuous variables were calculated at each time point. The results of the bivariate calculations are shown in Table 5. CSES and PV were significantly, negatively correlated at each timepoint of the intervention.
Table 5

_Bivariate Correlations at Week 1, Week 6, and Week 14_

<table>
<thead>
<tr>
<th>Measure</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Week 1</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. CSES</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>2. Perceived Stress</td>
<td>-.17**</td>
<td>--</td>
</tr>
<tr>
<td><strong>Week 6</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. CSES</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>2. Perceived Stress</td>
<td>-.24***</td>
<td>--</td>
</tr>
<tr>
<td><strong>Week 14</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. CSES</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>2. Perceived Stress</td>
<td>-.24***</td>
<td>--</td>
</tr>
</tbody>
</table>

Note: 1. = CSES, Career Search Self-Efficacy Scale (Solberg et al., 1994); 2 = Perceived Stress, Personal Vulnerability Subscale of the Stress Overload Scale Short Form (Amirkhan, 2018); *indicates \( p < .05 \); ** indicates \( p < .01 \); and *** indicates \( p < .001 \).

**Primary Analysis**

The results of the repeated measures MLM and the logistic regression are broken down by each research question.

**RQ 1**

A repeated measures multilevel model was used to determine if the CSES scores of undergraduate engineering students changed over the course of a semester in a STEM career planning course. This model served as the null model. The ICC was .16, which is above the .05 threshold, indicating that multilevel modeling was an appropriate analysis because of sufficient clustering in the data (Garson, 2019). Thus, 16% of the variance in CSES scores were explained between students and 84% of the variance were explained within individual students. Since the ICC was greater than .05, more predictors were added to the model and the AIC and BIC scores were calculated to indicate improved model fit. Moreover, there was missingness in the data. Data were missing at random (MAR) in that some participants only answered the survey at one or two timepoints of the intervention but not all three. Thus, maximum likelihood expectation
was used to include participants who completed the survey at least once during the intervention.

The results of the null model are presented in Table 6.

According to the results of the null model there does not appear to be a significant change in CSES scores over time \( (p = .77) \). However, the mean CSES scores did increase slightly between week 1, week 6, and week 14 (see Table 4).

Table 6

**Null Model of Repeated Measure MLM**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Null Model ( \beta )</th>
<th>SE</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>163.99***</td>
<td>8.48</td>
<td>[147.37, 180.62]</td>
</tr>
<tr>
<td>Time</td>
<td>1.11</td>
<td>3.79</td>
<td>[-6.32, 8.54]</td>
</tr>
</tbody>
</table>

**Variance Components**

<table>
<thead>
<tr>
<th></th>
<th>Var. in Intercept</th>
<th>387.73</th>
<th>[897.02, 2483.45]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Var. in Residuals</td>
<td>483.81</td>
<td>[7253.37, 9154.14]</td>
</tr>
</tbody>
</table>

**Fit Statistics**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ICC</td>
<td>.16</td>
</tr>
<tr>
<td>AIC</td>
<td>10211.12</td>
</tr>
<tr>
<td>BIC</td>
<td>10230.11</td>
</tr>
</tbody>
</table>

Note: \( N = 286 \), CSES = Career Search Self-Efficacy Scale (Solberg et al., 1994); Time = Week 1, Week 6, and Week 14; and * indicates \( p < .05 \); ** indicates \( p < .01 \); and *** indicates \( p < .001 \).

**RQ 2**

In order to determine if changes in CSES varied over the course of the semester in a STEM career planning course based on participants’ perceived stress, perceived stress was added to the repeated measures model as a predictor. The results are presented in Table 7. It is important to note that \( N = 285 \) in this model when compared with the \( N = 286 \) in the null model of maximum likelihood expectation. The model lost one participant who did not respond to the measure of perceived stress at least once. The results indicated that including perceived stress as a predictor of CSES over time resulted in a better fit for the data when compared with
the null model. The BIC score decreased 2,913.88 units. Raftery (1995) explained that a greater than 10-point reduction in BIC values suggests strong evidence for superior model fit.

In order to account for the sample’s average perceived stress, the researcher included the average perceived stress score of participants in the sample as a predictor. However, this variable was omitted from the model due to multicollinearity. Also, the researcher added the interaction between perceived stress and time as a covariate; however, the interaction was not significant ($p = .96$) and showed reduced model fit (i.e., the AIC and BIC scores increased). In addition, the researcher tested the random slope of perceived stress and the random slope of CSES. Although, the random slopes of perceived stress and CSES were each significant ($p < .001$), the models’ BIC values increased substantially. Thus, the researcher utilized the final model in Table 7 to test the assumptions of the repeated measures MLM and develop a final, robust model.

Table 7

Repeated Measures MLM with Perceived Stress and Time as Predictors of CSES

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Repeated Measures MLM Model</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>SE</td>
<td>95% CI</td>
</tr>
<tr>
<td>Intercept</td>
<td>176.77***</td>
<td>6.09</td>
<td>[164.84, 188.71]</td>
</tr>
<tr>
<td>Perceived Stress</td>
<td>-1.55***</td>
<td>.44</td>
<td>[-2.41, -.69]</td>
</tr>
<tr>
<td>Time</td>
<td>25.29***</td>
<td>2.11</td>
<td>[21.17, 29.43]</td>
</tr>
</tbody>
</table>

Variance Components

<table>
<thead>
<tr>
<th></th>
<th>Var. in Intercept</th>
<th>Var. in Residuals</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1205.88</td>
<td>1730.09</td>
<td></td>
</tr>
</tbody>
</table>

Fit Statistics

<table>
<thead>
<tr>
<th></th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>7293.61</td>
<td>7316.23</td>
</tr>
</tbody>
</table>

Note: $N = 285$, CSES = Career Search Self-Efficacy Scale (Solberg et al., 1994); Perceived Stress = Personal Vulnerability Subscale of the Stress Overload Scale Short Form (Amirkhan, 2018); Time = Week 1, Week 6, and Week 14; * indicates $p < .05$; ** indicates $p < .01$; and *** indicates $p < .001$. 

67
First, a histogram of the standardized conditional residuals was developed to assess non-normality of the residuals (See Appendix A). The histogram provided some evidence of non-normality of the standardized conditional residuals. Next, a boxplot of the standardized conditional residuals was developed and provided evidence of outliers in the data (See Appendix A). Following, the residual vs fitted (RVF) plot was examined (See Appendix A) and showed evidence of funneling or heteroscedasticity (Acock, 2018). Due to the violation of the assumptions for MLMs, the researcher compared the null model, the final model (see Table 7), the robust model, and the model with outliers greater than 1.96 removed (Garson, 2019). None of the predictors significantly changed (See Appendix A). Thus, the results of the robust model are displayed in Table 8.

Perceived stress was a significant, negative predictor of CSES ($p < .01$). Thus, as perceived stress scores increased, CSES scores decreased by 1.55 at each timepoint. Interestingly, time (i.e., week 1, week 6, and week 14) was a significant, positive predictor of CSES after accounting for perceived stress ($p < .001$). Thus, CSES scores increased by 25.29 units at week 1, week 6, and week 14. The final robust model explains 70% more variance in changes in CSES scores when compared to the null model. A graph of the change in CSES scores over the course of the semester is shown in Figure 4.
Table 8

Robust Repeated Measures MLM with Perceived Stress and Time as Predictors of CSES

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Repeated Measures MLM Model</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Parameter</strong></td>
<td><strong>β</strong></td>
<td><strong>SE</strong></td>
<td><strong>95% CI</strong></td>
</tr>
<tr>
<td>Intercept</td>
<td>176.77***</td>
<td>6.34</td>
<td>[164.34, 189.20]</td>
<td></td>
</tr>
<tr>
<td>Perceived Stress</td>
<td>-1.55**</td>
<td>.47</td>
<td>[-2.48, -.62]</td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>25.29***</td>
<td>2.30</td>
<td>[20.79, 29.80]</td>
<td></td>
</tr>
<tr>
<td><strong>Variance Components</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var in Intercept</td>
<td>1205.88</td>
<td>184.23</td>
<td>[893.85, 1626.84]</td>
<td></td>
</tr>
<tr>
<td>Var in Residuals</td>
<td>1730.09</td>
<td>208.41</td>
<td>[1366.26, 2190.81]</td>
<td></td>
</tr>
<tr>
<td><strong>Fit Statistics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>7293.61</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>7316.23</td>
<td></td>
<td></td>
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<tr>
<td>$R^2$</td>
<td>.70</td>
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<td></td>
</tr>
</tbody>
</table>

Note: N = 285, CSES = Career Search Self-Efficacy Scale (Solberg et al., 1994); Perceived Stress = Personal Vulnerability Subscale of the Stress Overload Scale Short Form (Amirkhan, 2018); Time = Week 1, Week 6, and Week 14; * indicates $p < .05$; ** indicates $p < .01$; and *** indicates $p < .001$. 
To determine the relationship CSES scores had with predicting students’ odds of persisting in their engineering major for the following semester, a logistic regression was conducted. This analysis included the end-of-semester (week 14) timepoint for one cohort (Fall 2019) of the intervention ($N = 100$). A binary logistic regression was performed with CSES as the independent variable and participants’ self-reported, high or low likelihood of continuing in an engineering major, as the dependent variable (See Table 9).
Table 9

Logistic Regression of CSES Scores Predicting Students Odds of Persisting in an Engineering Major

<table>
<thead>
<tr>
<th>Outcome Variable (Persist in Major)</th>
<th>β</th>
<th>SE</th>
<th>df</th>
<th>OR</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSES</td>
<td>.01*</td>
<td>.004</td>
<td>1</td>
<td>1.01</td>
<td>[.00, .02]</td>
</tr>
<tr>
<td>Intercept</td>
<td>-.40</td>
<td>.90</td>
<td>1</td>
<td>.67</td>
<td>[-2.16, 1.35]</td>
</tr>
</tbody>
</table>

Note: N = 100, CSES = Career Search Self-Efficacy Scale (Solberg et al., 1994); Persist in Major = 0 – Low Likelihood 1 – High Likelihood; * indicates p < .05; ** indicates p < .01; and *** indicates p < .001.

The logistic regression yielded statistically significant results. CSES scores were a significant, positive predictor of participants’ odds of persisting in an engineering major. A one unit increase in CSES scores was predictive of 1.01 higher odds of persisting in an engineering major (p < .05). Further, a one standard deviation increase in CSES increases the odds of persisting in an engineering major by 93%. At the mean CSES score (m = 228.77), the predicted probability of persisting in an engineering major was 88% with a 95% confidence interval between .81 and .94 (p < .001). The Cox and Snell pseudo $R^2$ value for this model was .06. In regards to specificity and sensitivity; originally, the model accurately predicted 85% of the cases. However, the model had difficulty predicting true negatives (i.e., specificity). The model was only able to predict 7.14% of the true negative cases. After reviewing the sensitivity and specificity plot, the probability cutoff was changed from Stata’s default setting of .5, to .8 in order to optimize specificity and sensitivity estimates. After changing the cutoff, overall the model accurately predicted 80% of the cases and accurately predicted 87.21% of true positives (sensitivity) and 35.71% of true negatives. The hat squared statistic was not significant ($p = .29$), indicating that the model was correctly specified. Additionally, the model did not violate the Hosmer and Lemeshow test ($p = .20$), indicating good model fit. Furthermore, the logistic
regression model yielded a chi-square statistic of 74.57 ($df = 1, p < .05$). A scatterplot of the outliers revealed one potential outlier. However, this outlier did not substantially change the results when removed so it was retained in the model in order to maintain the sample size. Lastly, with a VIF of 1, the model showed no signs of multicollinearity.

**Exploratory Model**

As an exploratory analysis, the researcher examined changes in CSES based on demographic factors including race; ethnicity; gender; first-generation status; and career advising and mock interviewing ratings. Though the model was significant, there were no significant changes in CSES scores over the course of the semester based on race ($p = .47$), ethnicity ($p = .17$), gender ($p = .87$), and first-generation status ($p = .79$). Each categorical group was compared with the dominant group. For example, the CSES scores of all racial groups were compared with participants who identified as White.

Regarding the relationship career advising and mock interview appointments had with CSES over time, participants’ ratings of the helpfulness of their career advising and mock interview appointments were added to the null model in a hierarchical fashion. Similar to the model presented in Table 8, the histogram, boxplot, and RVF plot showed evidence to suggest non-normality of the standardized conditional residuals and outliers (See Appendix A). The model presented in Table 10 was compared with outliers removed and the standard model. The significance of the predictors did not drastically change; however, to report the least biased estimates, the robust model is presented in Table 10. The results suggest that CSES scores significantly, positively increased 24.15 points at weeks one, six, and fourteen ($p < .05$). In addition, participants who rated their career advising appointment as more helpful were more likely to increase their CSES scores 14.57 points at weeks one, six, and fourteen ($p < .05$).
Though approaching significance, mock interviewing appointment ratings also had a positive relationship with CSES scores ($p = .08$) which suggests that as mock interview appointment ratings increased, CSES scores increased over time. The researcher also tested the interaction between career advising ratings and mock interview ratings. Though the interaction was significant ($p < .05$), the AIC scores decreased by 1 value while the BIC scores increased by almost 4 values. Thus, providing evidence of reduced model fit (See Table 11). When compared to the null model, the final robust model in Table 10 explains 66% more variance in CSES scores over time.

Table 10

*Robust Repeated Measures MLM with Time and Career Services Appointments as Predictors of CSES*

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Repeated Measures MLM Model</th>
<th>$\beta$</th>
<th>SE</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td></td>
<td>82.48*</td>
<td>37.03</td>
<td>[9.90, 155.05]</td>
</tr>
<tr>
<td>Career Ad</td>
<td></td>
<td>14.57*</td>
<td>5.34</td>
<td>[4.10, 25.04]</td>
</tr>
<tr>
<td>Mock Int</td>
<td></td>
<td>8.68</td>
<td>5.02</td>
<td>[-1.15, 18.51]</td>
</tr>
<tr>
<td>Time</td>
<td></td>
<td>24.15*</td>
<td>11.12</td>
<td>[2.17, 46.13]</td>
</tr>
</tbody>
</table>

**Variance Components**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>734.62</th>
<th>512.58</th>
<th>[183.13, 2883.96]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var in Intercept</td>
<td></td>
<td>2568.68</td>
<td>769.90</td>
<td>[1427.54, 4622.09]</td>
</tr>
<tr>
<td>Var in Residuals</td>
<td></td>
<td>734.62</td>
<td>512.58</td>
<td>[183.13, 2883.96]</td>
</tr>
</tbody>
</table>

**Fit Statistics**

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>2045.59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>2064.95</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>.66</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: $N = 186$, CSES = Career Search Self-Efficacy Scale (Solberg et al., 1994); Career Ad = Career Advising Rating; Mock Int = Mock Interview Rating; Time = Week 1, Week 6, and Week 14; * indicates $p < .05$; ** indicates $p < .01$; and *** indicates $p < .001$. 

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Figure 5. Plot of Predicted Change in CSES Scores Over Time. This figure demonstrates a margins plot of change in CSES scores over the course of a semester after accounting for career advising ratings and mock interview ratings.

Notes, N = 186 students in STEM Career Planning Course. Time 1 = Week 1, Time 2 = Week 6, Time 3 = Week 14
Table 11

Robust Repeated Measures MLM with Time, and Career Services Appointments Interactions as Predictors of CSES

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Repeated Measures MLM Model</th>
<th>β</th>
<th>SE</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td></td>
<td>201.22***</td>
<td>63.87</td>
<td>[76.04, 326.40]</td>
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<tr>
<td>Career Ad</td>
<td></td>
<td>-27.36</td>
<td>20.10</td>
<td>[-66.76, 12.03]</td>
</tr>
<tr>
<td>Mock Int</td>
<td></td>
<td>-31.03</td>
<td>18.53</td>
<td>[-67.35, 5.29]</td>
</tr>
<tr>
<td>Career AdxMock Int</td>
<td></td>
<td>12.89*</td>
<td>6.10</td>
<td>[.93, 24.86]</td>
</tr>
<tr>
<td>Time</td>
<td></td>
<td>26.70*</td>
<td>11.08</td>
<td>[4.99, 48.12]</td>
</tr>
</tbody>
</table>

Variance Components

<table>
<thead>
<tr>
<th>Variance Components</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Var in Intercept</td>
<td></td>
<td>851.96</td>
<td>546.15</td>
<td>[242.52, 2992.82]</td>
</tr>
<tr>
<td>Var in Residuals</td>
<td></td>
<td>2412.31</td>
<td>776.57</td>
<td>[1283.56, 4533.68]</td>
</tr>
</tbody>
</table>

Fit Statistics

<table>
<thead>
<tr>
<th>Fit Statistics</th>
<th></th>
<th>AIC</th>
<th></th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td></td>
<td>2044.85</td>
<td></td>
<td>2067.43</td>
</tr>
<tr>
<td>R²</td>
<td></td>
<td>--</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: N = 186, CSES = Career Search Self-Efficacy Scale (Solberg et al., 1994); Career Ad = Career Advising Rating; Mock Int = Mock Interview Rating; Career AdxMock Int = Interaction between Career Advising Rating and Mock Interview Rating, Time = Week 1, Week 6, and Week 14; and * indicates p < .05; ** indicates p < .01; and *** indicates p < .001.

Conclusion

This chapter discussed several statistical analyses, including descriptive statistics, means, standard, bivariate correlations, repeated measures MLM results, and logistic regression results. In sum, the results suggested that participating in a STEM career planning course was associated with positive changes in CSES overtime. Though the main effect of mock interview appointment rating was approaching significance, the results provided some evidence that attending career services appointments (i.e., career advising appointments and mock interview appointments) had
a positive relationship with building the CSES of undergraduate students in the STEM career planning course.

Regarding the first research question, statistical significance was not found. However, average CSES did slightly increase from the beginning to the end of the semester. The statistical analysis of research question two yielded significant results. The results suggested that perceived stress significantly, negatively predicted changes in CSES scores over time. In addition, after including perceived stress as a predictor, CSES scores showed a statistically significant change over the course of the semester. Thus, providing evidence that participating in a STEM career planning course was associated with increased CSES scores over the course of the semester. Lastly, for research question three, higher CSES scores were associated with participants’ increased odds of persisting in an engineering major.

These results provided support for STEM career planning courses as impactful career development interventions. Additionally, these results show the hindrance that increased levels of perceived stress pose in developing undergraduate engineering students’ career-related self-efficacy. Further discussion of the study’s implications are presented in Chapter Five, along with a discussion of the limitations and directions for future research.
Chapter Five

Discussion

The issue of undergraduate STEM attrition is of national and local concern. In order to increase the number of students completing undergraduate degrees in STEM, universities nationally are implementing academic, social, and career supports for students pursuing degrees in these fields. Locally, at VCU-COE, the professional development course offered to undergraduate engineering students aims to enhance students’ career development and skills surrounding networking with peers and employers; searching for jobs and internships; interviewing; and setting short and long-term career goals. The course is aimed at helping students to develop their professional identity as engineers and computer scientists. STEM career planning courses similar to the professional development course offered through the VCU-COE Engineering Career Services department are shown to increase engineering students’ retention in their major and reduce their negative career thoughts over the course of a semester (Belser et al., 2017; Prescod et al., 2018). This dissertation study aimed to examine the influence of a STEM career planning course on students’ career self-efficacy over the course of a semester, investigate how career self-efficacy is predictive of increased odds of persisting in an engineering major, and understand the relationship stress has with career self-efficacy in a STEM undergraduate population. While the previous literature supports STEM career planning courses as having a positive impact on students’ career development by reducing students’ negative career thoughts, there are other career development factors that had not yet been explored in the
literature (i.e., career self-efficacy). It is important to understand the relationship STEM career planning courses have with building undergraduate students’ career self-efficacy because self-efficacy beliefs are critical to helping individuals choose careers and set career goals (Lent, Brown, & Hackett, 1994). Further, with the increased stress that college students experience (ACHA, 2018) and the negative impacts stress can have on distorting ones’ self-efficacy beliefs (Bandura, 2005), it was important that the present study also explored the impact of students perceived stress on their career self-efficacy.

In accordance with the previous literature on STEM career planning courses, the intervention in this study did positively impact students’ career self-efficacy as measured by the CSES scale. In addition, in alignment with SCT and SCCT, perceived stress negatively impacted students CSES. Moreover, similar to the work of Belser and colleagues (2017), increases in CSES scores were associated with increased odds of persisting in an engineering major for another semester. This chapter, provides an in-depth discussion of the study’s findings and implications for the counselor education profession and future research.

**Research Question One**

**Career Search Self-Efficacy**

To answer research question one, this study examined changes in week 1, week 6, and week 14 CSES scores using a repeated measures MLM. This model served as the null model in which all other models were compared. The ICC indicated that a MLM approach was an appropriate statistical analysis due to sufficient clustering in the data. This suggests that the variance in CSES scores was not only influenced by the individual student but is also by the students’ interactions with their peers, instructor, and guest speakers in the course. The null model did not support the hypothesis that CSES would significantly, positively increase over the course of the semester. However, the mean CSES scores at week 1, week 6, and week 14 did
reveal that CSES increased over time \( (m = 165.13 \text{ [week 1]}, m = 166.20 \text{ [week 6]}, m = 167.33 \text{ [week 14]}) \).

**Research Question Two**

**Perceived Stress**

Utilizing the Personal Vulnerability subscale of the Stress Overload Short-Form Scale, this study examined the influence of perceived stress on CSES scores. The researcher hypothesized that perceived stress would have a significant, negative impact on CSES scores over time. The hypothesis for research question two was supported by the analysis. Adding perceived stress as a predictor of CSES not only made the model a better fit for the data, it also helped explain the relationship between CSES scores and time. In the final robust model, time was now a significant predictor of CSES. Thus, CSES scores did in fact, statistically significantly and positively increase over the course of the semester, after accounting for the role of perceived stress. At each timepoint (week 1, week 6, and week 14), CSES scores were predicted to increase more than 25 points for students in the Fall and Spring 2019 cohorts of this STEM career planning course. In relationship to perceived stress, a one unit increase in perceived stress would yield an almost two-point reduction in CSES scores at each timepoint.

The final robust model, explained 70% more variance in CSES scores when compared to the null model, suggesting a large practical effect size.

Not only were the findings that 1) CSES increased over the course of the semester and 2) perceived stress was associated with reduced CSES in support the researcher’s hypotheses, these findings also aligned with the SCT and SCCT framework. The previous work of Lent et al. (2008), Lent et al. (2013), and Lent et al. (2016) provided empirical support for SCCT as a theoretical framework that explains the career choice, performance, and goals of undergraduate
students majoring in STEM. However, none of those studies included an intervention. The intervention in this study provided students with sources of self-efficacy. For example, students were provided vicarious learning opportunities when their peers came into the course to share their experience working at an internship or when employers presented in the course about their experience hiring students from the same university. Further, students in the course were provided mastery experiences, in that students had to practice interviewing skills by conducting mock interviews with a career counselor and students had to practice networking skills by going to the university’s engineering career fair as a class requirement. Lastly, the instructor and career counselors often exposed students to verbal persuasion through encouraging students to reach their goals and discussing students’ strengths. These class experiences directly align with SCCT and provide the sources of self-efficacy that Bandura (1977) originally discussed. Thus, the finding that CSES scores did statistically increase of the course of the semester, supports SCCT as a career development theory that can applied to interventions for undergraduate students majoring in STEM.

Furthermore, the finding that perceived stress better explained changes in CSES scores over time also aligns with SCT and SCCT. Bandura (2008) also explained the unique relationship between self-efficacy and physiological states such as stress. The change in CSES scores over time may have only been significant after accounting for perceived stress because increases in stress can distort and undermine one’s self-efficacy beliefs. Although students in the course did receive a course lecture on stress and wellness, this was not enough to significantly reduce their self-reported perceived stress over an entire semester. Thus, students perceived stress significantly increased over the course of the semester and these increases in perceived stress were associated with decreases in CSES. To strengthen this STEM career planning course
intervention, it might be beneficial to incorporate more class activities, discussions, and reflections surrounding stress and reaching out for support.

For instance, Wise interventions focus on story editing and underscore three aspects of one’s appraise social situations (Walton & Wise, 2018). Wise interventions emphasize a) how people make sense of themselves and social situations plays a critical role in their behavior; b) key meanings can be altered with brief exercises; and c) altering meanings can lead to lasting change in one’s behaviors. Crum, Salovey, and Achor (2013) explained stress mindset and distinguished between a stress-is-enhancing mindset and a stress-is-debilitating mindset. A stress-is-enhancing mindset refers to the extent to which one believes that stress has enhancing effects for stress-related outcomes such as performance, productivity, learning, and growth. Conversely, an individual with a stress-is-debilitating mindset believes that stress has debilitating consequences for outcomes related to performance, productivity, learning, and growth. In their study, participants were randomly assigned to the stress-is enhancing mindset group and the stress is debilitating mindset group (i.e. control group). During the first week of a course, participants were shown videos related to stress enhancing and debilitating conditions related to health, performance, and growth. Following participants, completed the Stress Mindset Measure (SMM). The control group received no videos. The results of the generalize linear model showed that after reviewing the stress mindset videos, participants changed their mindsets about stress. Further, when compared to the control group, participants in the enhancing condition reported improved psychological symptoms and better work performance. Incorporating more in-class interventions surrounding stress-is enhancing mindsets may help to reduce students’ stress over the course of the semester and reduce the negative impact of perceived stress on students’ career self-efficacy beliefs.
Likewise, Regehr, Glancy, and Pitts (2013) did a meta-analysis of interventions used to reduce stress in university students. Their meta-analysis revealed that on-line psychoeducation trainings related to stress are associated with decreasing college students’ stress. For instance, Stress Inoculation Trainings (SIT) which include group training sessions; homework practice; and relaxation and guided imagery could be included as online homework assignments in STEM career planning courses. Including on-line interventions could allow students flexibility and allow for in-class time to be focused more on career development. In addition, their meta-analysis revealed that cognitive-behavioral/mindfulness interventions are promising interventions in the college student stress literature. Introducing students to progressive muscle relaxation and other mindfulness techniques are examples of coping skills that can be taught to students a couple times throughout the semester in a STEM career planning course.

**Research Question Three**

**Persistence**

Research question three referenced whether CSES was associated with students’ odds of persisting in an engineering major. Originally, the categorical item related to persistence had five categories. Students self-categorized how likely there were to enroll in an engineering major for the following semester from “1” indicating not likely at all to “5” indicating extremely likely. However, due to some categories with only one or two endorsements, these categories were collapsed into two categories, high likelihood (n = 86) and low likelihood (n = 14). Most students endorsed a high likelihood of continuing in the VCU-COE for the following semester. This finding was not surprising because this intervention included a mix of freshman to seniors. The literature regarding STEM major attrition typically discusses that students tend to leave their STEM major during their first or second year (Chen, 2014). Since this intervention was not
solely targeted at freshman and sophomores, it is not surprising that most students intended to continue in a VCU-COE major.

However, the results of the logistic regression suggested that increases in CSES scores were associated with higher odds of persisting in an engineering major. Though, the results supported the hypothesis that CSES scores would be a significant positive predictor of increased odds of persisting in an engineering major, the model had a small effect size. Thus, limiting the practical significance of the results. Additionally, the model was much better at predicting true positives. Thus, the model had lower accuracy predicting students who fell into the low likelihood category of continuing in an engineering major. The aforementioned limitations of this model are likely due to the lack of variability among the two categories. Though this model was sufficiently powered, the sample size for this analysis was reduced (N = 100) because the item related to persistence was only asked of the Spring 2019 cohort and the analysis only included their response at the end of the semester in order to align with course scheduling. Thus, conducting this analysis with a larger sample size in the future could produce more stable and robust results. Despite the limitations of the model, it did accurately predict 80% of the cases; therefore, providing some initial evidence that it is important to foster students’ career self-efficacy in order to increase their odds of persistence in STEM. Further, the finding that CSES positively predicted increased students’ odds of persistence was in accordance with previous literature. Belser et al. (2017) found that for first-year students, reductions in negative career thoughts were associated with increased odds of being retained in a STEM major during their second year. This model adds to the literature, that for students in a STEM career planning course, improvements to career development domains such as career self-efficacy are important to understanding persistence and retention.
Exploratory Analysis

Career Services

This dissertation also included an exploratory analysis outside of the three research questions. The researcher examined changes in CSES scores over the course of the semester based on demographic information such as race, gender, ethnicity, and first-generation status. The results yielded no significant differences in CSES based on the aforementioned demographics. This finding was unique when compared to the previous literature. Most studies suggest that URM (i.e., women in STEM, Black, Latinx, and Native Americans) are at an increased risk of not persisting in a STEM major (Chen, 2014, Estrada et al., 2016). However, Belser et al. (2018) found no statistical significance regarding the relationship gender had with predicting second year retention in a STEM major and surprisingly found that African-American and Hispanic students had higher odds of persisting in a STEM major. Thus, there is some evidence to suggest the impact of demographic factors on undergraduate students in STEM can vary in impact on outcomes. One potential reason that the demographics were not significant predictors of CSES may be that the intervention was the same for all students. Therefore, in regards to learning how to interview, learning how to search for a job, setting career goals, etc., all students received the same information and sources of building self-efficacy. In this way, the intervention could be viewed as an equalizer.

As another exploratory measure, the researcher examined the differences in CSES scores over time based on students’ ratings of their career advising and mock interview appointments. Students rated on two, 5-point Likert-type scale items, 1) how helpful their career advising appointment and 2) how helpful their mock interview appointment from 1- not helpful at all to 5- extremely helpful. Again, the results of this model suggested that CSES scores significantly,
positively increased over the course of the semester. In this model, CSES scores were predicted to increase more than 24 points at each timepoint. In addition, students rating of their career advising appointments was a significant, positive predictor of CSES scores; CSES scores were predicted to increase more than 14 points the higher students’ rated their career advising appointments as helpful. Although not statistically significant, this model suggested that higher ratings of students’ mock interview appointments were associated with higher CSES scores. Adding these career services appointments as predictors of CSES explained 66% more variance in CSES scores when compared with the null model, indicating a large practical finding.

The results also suggested that there may be shared variance between career advising ratings and mock interview ratings. The interaction between the two appointments was a positive and statistically significant predictor of CSES scores. However, when models become more complex, it is more conservative to examine the BIC values (Garson, 2019). The model which included the interaction between the career services appointments as predictors of CSES increased the BIC value by more than three points. Though this model was not a better fit for the data, it was explanatory. From a practitioner perspective, this interaction suggests that the combination of a) going to career advising and mock interview appointment and b) viewing those appointments may be helpful in building students career self-efficacy over time. Thus, both career advising and mock interviewing with a career counselor may be influential components of STEM career planning courses moving forward.

These exploratory findings also align with SCCT in that learning experiences directly impact one’s self-efficacy (Lent, Brown, & Hackett, 1994). Meeting with a career counselor for career advising and mock interviewing are learning experiences that allow students to reflect on themselves, their career choice, and their career goals. Particularly in career advising
appointments, students likely discuss how to search for a job, network, explore their interests, and interview. All of which are topics aligned with the CSES domains of job search efficacy, networking efficacy, interviewing efficacy, and personal exploration efficacy. Thus, these career services appointments can be prime learning opportunities that contribute to the development of positive self-efficacy beliefs.

**Implications for Counseling and Counselor Education**

Overall, these findings support STEM career planning courses as impactful interventions for students’ career development. The results provide many implications for counseling and counselor education. The results provide increased support that focusing on disparities in STEM degree attainment from a career development perspective may be an impactful intervention. At first glance counseling, counselor education, and disparities in the STEM workforce may seem unrelated. However, further examination of the studies implications reveals that counselors and counselor educators can play a vital role in supporting students pursuing careers in STEM.

**Counseling**

For career counselors at universities, interacting with undergraduate students during career advising, mock interviewing, and STEM career planning courses can have a positive influence on students career self-efficacy. Thus, the findings in this study suggest that it is beneficial for career counselors to be involved in STEM career planning courses. In previous studies done by Prescod et al. (2018) and Belser et al. (2017), the STEM career planning courses were taught by counselors. Although, counselors did not teach the STEM career planning course discussed in this study, the results suggest that students’ interactions with career counselors was beneficial to building their career self-efficacy. Thus, counselors should be a major component of STEM career planning courses even if not always as the instructor.
Further, the negative impacts that perceived stress had on students’ CSES, also supports the idea for more counseling-related interventions in STEM career planning courses. Although a career counselor guest lectured in the class regarding stress management tips and resources for handling stress, there is an opportunity to incorporate more stress psychoeducation and intervention into STEM career planning coursework. Career counselors can play a leadership role in providing both emotional and career support to students in STEM career planning courses. Though career services and personal counseling are typically separate entities on college campuses there is often an overlap between vocational and psychological problems (Schaub, 2012). Thus, career counselors should not shy away from discussing with students how their stress is impacting their career goals and self-efficacy beliefs.

Additionally, counselor’s involvement in STEM interventions does not have to begin at the college level. For instance, school counselors play an integral role in providing academic and career counseling services to K-12 students (Schmidt, Hardinge, & Rokutani, 2012). The American School Counseling Association (ASCA) provides a National Model to school counselors on how they can support students’ career development (ASCA, 2019). According to Winston-Byars (2014), school counselors are career development professionals (CDPs) along with other professionals who have training from the National Career Development Association (NCDA). As CDPs, school counselors are uniquely primed to deal with the diversity of issues in STEM education and career attainment. However, in regards to STEM industries and their importance in the U.S. economy, Schmidt and colleagues (2012) explain that school counselors often have an “unconscious incompetence” (p. 27). Thus, school counselors may be missing opportunities to encourage students to pursue post-secondary STEM majors (Hall et al., 2011). This lack of knowledge about STEM career opportunities is a barrier to school counselors playing a more involved role in the “STEM Crisis.” However, career development research like
the present study can help build the body of knowledge surrounding what counselors can do to support students pursuing STEM. Even at the secondary level, school counselors can provide students with learning experiences similar to those in the present study’s STEM career planning course. For instance, school counselors can expose students to employers in STEM fields through career days. School counselors can help students develop job search and networking skills during their classroom presentations. In addition, school counselors can provide students with vicarious learning opportunities by connecting K-12 students with local undergraduate students majoring in STEM through mentorship programs.

**Counselor Education**

Not only does this dissertation have implications for counseling, this study also has several implications for counselor educators as both educators and researchers. Counselor educators’ involvement in research aimed at investigating the impact of STEM-focused career interventions (i.e., STEM career planning courses) on students’ career development and retention can help increase the STEM-related knowledge of career counselors, school counselors, and other CDPs. Additionally, the federal government has invested 200 million dollars in STEM education and research (US Department of Education, 2019). Thus, counselor education research endeavors that align with federal and state STEM-related agendas can provide external funding opportunities to support research at the intersection of career counseling and development and STEM interventions.

Additionally, by introducing the role of stress, this study further establishes the need for counselors’ involvement in STEM initiatives. Counselor educators can play an important role in teaching counselors-in-training (CIT) how to address both mental health and career development concerns when working with students pursuing STEM degrees and careers. Although in this study, there were no race or gender differences in overall changes in CSES, this study included a
predominantly white-male sample which is consistent with the STEM literature and trends. Yet, the counseling profession’s dedication to diversity and multiculturalism (ACA, 2014) adds to the role counselors can play in promoting STEM careers. Given the lack of racial and gender diversity in STEM undergraduate degree programs and the STEM workforce (Dailey & Eugene, 2013; Estrada, et al., 2016), counselors can support marginalized students during their pursuit of careers in STEM. Likewise, counselor educators can play a direct role in developing CITs’ knowledge surrounding the racial and ethnic disparities in STEM fields in order to help CITs develop the multicultural competence needed to support minority students (Byars-Winston, 2014). Thus, the multicultural training of counselors uniquely positions counselors as direct supports for underrepresented students during their pursuit of careers in STEM industries.

One way in which counselor educators can build the multicultural competence of CIT as it relates to STEM and career development is through career counseling coursework. Since career counseling is one of the Council for Accreditation of Counseling and Related Educational Programs’ (CACREP, 2019) core content areas and the NCDA (2015) requires that all career professionals maintain cultural awareness and sensitivity, counselor educators can provide lectures that discuss the gender and racial disparities in the STEM labor markets and the role of counselors in closing those gaps. As part of career counseling coursework, counselor educators can provide CIT with industry-specific knowledge in order to help students understand labor market trends, the role of counselors as CDPs, and the barriers that underrepresented students and employees may face in various industries. Rather than solely giving general career development training, counselor educators can include STEM as an industry of emphasis in career counseling coursework.

Specifically, research suggests that for Black students in STEM, higher reports of a strong science identity and reporting low instances of discrimination result in a higher likelihood
of being retained in STEM (Osegeura, Ju Park, Javiera De Los Rios, Apracio, & Johnson, 2019). Thus, as part of career counseling coursework, counselor educators can increase CITs’ awareness of STEM as an industry and also emphasis the importance of a) supporting racially minoritized students who may face discrimination and b) helping students to develop an identity in STEM. Further, for Black women in STEM factors such as early exposure to STEM, interest in STEM, parental support, and commitment to engineering, all contribute to their pursuit of undergraduate degrees in engineering (Stitt Richardson, Guy, & Perkins, 2019). Thus, in career counseling courses, counselor educators can help CIT a) identify how they would foster parental support, b) examine what role they play in helping to increase and advocate for URM students’ early exposure to STEM, and c) examine how they can help students to assess their commitment to STEM as a career path.

**Limitations**

Despite the contributions this study makes to the STEM career development literature, this dissertation study has several limitations. One limitation was the lack a control group and random assignment; therefore, causation could not be determined. Additionally, without random assignment, selection bias was a threat to external validity in that there may be something unique about the students at VCU who take this class that limits the generalizability of the findings. Another threat to validity was social desirability, in that participants may have responded to survey items based on how they think they should answer rather than answering based on what is true for them. Additionally, testing threat might have caused participants to score better on the mid- and end-of-semester tests solely because they took the survey in the beginning of the course. Furthermore, experimental mortality was another threat to validity – many participants completed one or two of the survey iterations but not all three. Consequently, the number of participants completing the survey fluctuated between timepoints. Lastly, history or maturation
were threats to external validity - outside events or processes unrelated to the intervention might have impacted students’ end-of-semester CSES scores.

**Recommendations for Future Research**

There are several ways in which future research can build from the findings in this study. First, future studies can collaborate with academic advising to help randomly assign students to STEM career planning courses and a control group to investigate the differences in career development and retention outcomes for students who are not in a STEM career planning course and students who are in a STEM career planning course. In addition, future research can explore the study’s variables at multiple timepoints from multiple universities. These recommendations for future research would help establish causality and increase the generalizability of the study’s findings.

In order to further support undergraduate students majoring in STEM, future research could examine how including multiple stress and mindfulness psychoeducation interventions in a STEM career planning course changes the relationship between perceived stress and CSES. Additionally, Bandura (2008) also explained that increases in anxiety can negatively impact self-efficacy beliefs. Thus, to further understand the impact of mental health on the career self-efficacy of students majoring in STEM, future studies can investigate the impact of anxiety.

To further build on the career self-efficacy literature, future studies can explore the how participating in a STEM career planning course influences other forms of career self-efficacy such as career decision-making self-efficacy. In addition, to further align with SCCT and understand self-efficacy, future studies can examine the perceived barriers of students majoring in STEM and how those barriers (e.g. financial, social, motivation) impact their self-efficacy beliefs and persistence in their major. Moreover, the logistic regression was better at using CSES scores to predict the odds of persistence for students who were categorized as likely to continue
in their major. In order to better predict students’ odds of not persisting in the major, future research can include a larger sample size that allows for covariates such as gender and race to be added to the logistic regression model. Likewise, future studies can use other career self-efficacy predictors (i.e., CDMSE) to predict students odds of persisting in their major because perhaps, CSES is only helpful in identifying students who are not at risk of leaving their major.

Further, the participants were asked to categorize their likelihood to enroll the following semester; however, there was no evidence that the students in the sample actually enrolled. Thus, a follow-up study could be done to track the students who continued the following semester and for those who did not enroll, qualitative methods could be used to understand why they left their major. Lastly, in order to prevent attrition early on, future research can provide STEM-interested K-12 students with career development interventions before college and longitudinally track students throughout their undergraduate journey. This would allow for a firmer understanding of the long-term effects of STEM career planning interventions in relation to STEM degree and career attainments.

Conclusion

This study provides encouraging results regarding the impact of STEM career planning courses on undergraduate engineering students’ career search self-efficacy and persistence in their major. The literature on STEM career planning courses is limited. Rather than focusing on reducing negative career thoughts, this study adds to the literature by exploring the impact of a STEM career planning course on students’ career search self-efficacy. This study also adds to the STEM career planning literature by introducing the influence of perceived stress. Introducing perceived stress not only allowed for a better understanding of undergraduate engineering students’ career search self-efficacy, examining perceived stress further solidified a role of counselors in STEM interventions. The training of counselors allows them to address students’
concerns related to stress while also helping students’ career development. The demands for
STEM professional are only growing. Counselors can be a part of developing the next generation
of STEM professionals that are emotionally healthy and self-efficacious in their career choice
and goals. Through their involvement in STEM career planning, counselors can help address and
intervene on the STEM Crisis.
References


105


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<th>CSES Alignment</th>
<th>SCCT Alignment</th>
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<td>Every student will schedule and complete a career advising session with the College of Engineering Career Services office</td>
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<td>Interviewing</td>
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<td>------------------------------------------------------</td>
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<td>Attendance and Reflections</td>
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<td>Vicarious Learning and Physiological Arousal</td>
<td>Personal Exploration, Networking, Job Search, and Interviewing</td>
<td>Choice Interest, Goals, and Performance</td>
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Appendix A

STATA Multilevel Model Power Analysis Output
A priori power analysis

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..............................100
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covariate type: continuous
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number of converging runs: 100
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Assumptions for model with perceived stress and time as predictors of CSES
. estimates table model1 model2 model4 model5, star

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legend: * p<0.05; ** p<0.01; *** p<0.001

Full Code

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estat ic
estat icc
estimates store model1
mixed cses_total time pv|| recordid:, mle
estat ic
estimates store model2

*Assumptions*
predict Resid_cs, rstandard
histogram Resid_cs, normal
graph box Resid_cs
predict double Pred_c, fitted
scatter Resid_cs Pred_c
mixed cses_total time pv_total|| recordid:, vce(robust)
estimates store model3
gen outlier = .
replace outlier = 1 if Resid_cs > 1.95999
replace outlier = 0 if Resid_cs < 1.96
fre outlier
mixed cses_total time pv_total|| recordid: if outlier == 0,
estimates store model4
estimates table model1 model2 model3 model4, star

*Final Model*
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estat ic

*Final Model Plot*
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marginsplot, title ("Predicted Change in Career Search Self-Efficacy Scores at Week 1, Week 6, and Week 14")caption("Notes, N = 285 students in STEM Career Planning Course. Time 1 = Week 1, Time 2 = Week 6, Time 3 = Week 14")scheme(s2color)ytitle("Predicted CSES Score", size (medium))xtitle("Time")
marginsplot, title ("Predicted Change in Career Search Self-Efficacy Scores at Week 1, Week 6, and Week 14")caption("Notes, N = 285 students in STEM Career Planning Course. Time 1 = Week 1, Time 2 = Week 6, Time 3 = Week 14")scheme(s2color)ytitle("Predicted CSES Score", size (small))xtitle("Time")
marginsplot, title ("Predicted Change in CSES Over Time")caption("Notes, N = 285 students in STEM Career Planning Course. Time 1 = Week 1, Time 2 = Week 6, Time 3 = Week 14")scheme(s2color)ytitle("Predicted CSES Score", size (small))xtitle("Time")
marginsplot, title ("Predicted Change in CSES Over Time")caption("Notes, N = 285 students in STEM Career Planning Course. Time 1 = Week 1, Time 2 = Week 6, Time 3 = Week 14")scheme(s2color)ytitle("Predicted CSES Score", size (small))xtitle("Time")

*RQ 3 Logistic Regression and Assumptions*
tab persist_major
quietly misstable summarize persist_major _race _hispanic _gender first_gen, gen(miss > `_)
describe miss_*
sum miss_*
logistic miss_*
clonevar persist2 = persist_major
recode persist2 (5 = 1) (1 2 3 4 = 0)
logit persist2 cses_total
logit persist2 cses_total, or
margins, atmeans
listcoef
listcoef, help percent
estat gof, g(10) table
lsens
estat classification, cutoff(.80)
linktest
predict p
predict db, dbeta
scatter db p
scatter db p, mlabel(recordid)
fitstat
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*Exploratory MLM w/ Career Services Appointments*
mixed cses_total time|| recordid:, mle
estat ic
mixed cses_total time career_advise mock_int|| recordid:, vce(robust)
estat ic
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marginsplot
*Exploratory MLM w/ Career Services Appointments Interaction*
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estat ic
. ipdpower, sn(100) ss1(558) ss2(183) b0(0) b1(.5) b2(.3) b3(.3) minsh(3) cexp

model 1: standard regression
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covariate type: continuous
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computational time (min): .

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within-sd(error): .
R^2(%): 29.983

Results: coverage

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Assumptions for model with time, and career services appointments as predictors of CSES
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legend: * p<0.05; ** p<0.01; *** p<0.001

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legend: * p<0.05; ** p<0.01; *** p<0.001
Appendix B

Institutional Review Board

TO: Philip Gnilka
    Jose Alcaine
    Philip Gnilka
    Autumn Randell

CC: 

FROM: VCU IRB Panel A
      Philip Gnilka ; HM20018417

RE: A longitudinal study of the influence of a STEM career planning course and perceived stress on career search self-efficacy and retention in engineering undergraduate students

To be subject to the regulations, a study must meet the definitions for BOTH “human subject” AND “research”. While your study may fit one of these definitions, it does not fit both. Therefore, your study is not subject to the regulations and no IRB review or approval is required before you proceed with your study.

Section 45 CFR 46.102(l) of the HHS Regulations for the Protection of Human Subjects defines research as “a systematic investigation, including research development, testing and evaluation, designed to develop or contribute to generalizable knowledge. Activities which meet this definition constitute research for purposes of this policy, whether or not they are conducted or supported under a
program which is considered research for other purposes.”
Section 45 CFR 46.102(e)(1) of the HHS Regulations for the Protection of Human

Subjects defines a **human subject** as “a living individual about whom an investigator conducting research:

- Obtains information or biospecimens through intervention or interaction with the individual, and uses, studies, or analyzes the information or biospecimens; or
- Obtains, uses, studies, analyzes, or generates identifiable private information or identifiable biospecimens.”

Thank you for informing us of the project. If we can be of service with respect to future research studies, please contact us.

If you have any questions, please contact the Office of Research Subjects Protection (ORSP) or the IRB member(s) assigned to this review. Reviewer contact information is available by clicking on the Reviewer’s name at the top of the study workspace.

Thank you for your continued collaboration in maintaining VCU’s commitment to protecting human participants in research