EXAMINING THE INFLUENCE OF STEM COLLEGE PROGRAM PARTICIPATION ON ENGINEERING PERSISTENCE AMONG FIRST-GENERATION COLLEGE STUDENTS IN ENGINEERING

A Dissertation

presented to

the Faculty of the Graduate School

at the University of Missouri-Columbia

In Partial Fulfillment

of the Requirements of the Degree

Doctor of Philosophy

by

DAVID DIAZ

Dr. Lisa Flores, Dissertation Supervisor

July 2021

The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled

EXAMINING THE INFLUENCE OF STEM COLLEGE PROGRAM PARTICIPATION ON ENGINEERING PERSISTENCE AMONG FIRST-GENERATION COLLEGE STUDENTS IN ENGINEERING

presented by David Diaz,

a candidate for the degree of doctor of philosophy,

and hereby certify that, in their opinion, it is worthy of acceptance.

____
Professor Lisa Y. Flores

____
Professor Patrick J. Rottinghaus

____
Professor Brittany Beasley

____
Professor Casandra Harper Morris

ACKNOWLEDGEMENTS

I greatly appreciate and thank everyone who has helped me reach this point in my personal and professional life. First and foremost, I want to thank my advisor and dissertation chair, Dr. Lisa Flores, for her great amount of support from the very start of my doctoral training to this recent milestone. It has been a privilege and joy working with and getting support from you across different doctoral training activities. Second, I want to thank my committee members, Dr. Patrick Rottinghuas, Dr. Brittany Beasley, and Dr. Casandra Harper Morris for the support and feedback throughout this process. Third, I want to thank my other doctoral training supervisors and other staff who were very encouraging and supportive throughout the years and with this dissertation process. Fourth, I appreciate those pre-doctoral training educators, supervisors, and mentors who had an influential role in helping me reach this point in my professional development. This point in my professional journey would not be possible without those educators/mentors who helped me attend and succeed in college where I was inspired to continue on to graduate training. Lastly, I would like to thank my family and friends for their on-going support throughout the years. This has been a long journey that was made possible by you all.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

STEM	Science, Technology, Engineering, and Mathematics
FGCS	First Generation College Students
CGCS	Continuing Generation College Students
SCCT	Social Cognitive Career Theory
ESE	Engineering Self-Efficacy
NOES-E	Negative Outcome Expectations Scale– Engineering
EPI	Engineering Persistence Intentions
SEM	Structural Equation Modeling

EXAMINING THE INFLUENCE OF STEM COLLEGE PROGRAM PARTICIPATION ON ENGINEERING PERSISTENCE AMONG FIRST-GENERATION COLLEGE STUDENTS IN ENGINEERING

David Diaz

Dr. Lisa Flores, Dissertation Supervisor

ABSTRACT

The present study used Social Cognitive Career Theory (SCCT; Lent et al., 1994; Lent et al., 2000) to examine the influence of college STEM (science, technology, engineering, and mathematics) program participation on engineering persistence among first-generation college students (FGCS) in engineering. Data for the present study came from a larger longitudinal study on engineering students that collected data from a quantitative (Qualtrics) survey during Spring 2015 and Spring 2016 across 11 universities in the United States. Participants for this present study were 473 FGCS (73.4% Latinx and 26.6.% White) across different undergraduate class standings pursuing an engineering degree. Participants in the present study were considered FGCS if neither of their parents had obtained a 4-year college degree. Results suggested some support for SCCT proposed social-cognitive relationships among this sample of Latinx and White FGCS pursuing an engineering degree. In addition, results indicated that FGCS who participated in college STEM programs needed lower level of engineering goals to persist in engineering compared to those who did not participate in college STEM programs. Practical and research implications, limitations, and future directions are discussed.

Chapter 1

Introduction

There is an increasing demand for professionals in science, technology, engineering, and mathematics (STEM) careers (U.S. Bureau of Labor Statistics, 2017). A high number of jobs in the United States (U.S.) require STEM related skills (National Science Board, 2018). Engineering employment, for instance, is projected to grow over the next several years, increasing the demand for qualified engineers (Torpey, 2018). Approximately 139,000 new engineering jobs have been projected between 2016 and 2026, with civil, mechanical, and industrial engineering positions accounting for approximately 36 percent of those new jobs (Torpey, 2018). Increasing the STEM workforce is considered important to the U.S. for having a robust economy and being globally competitive (National Science Board, 2018). U.S. government officials have noted the importance of increasing recruitment and retention strategies targeting college students in STEM fields (President's Council of Advisors on Science and Technology, 2012). Even within U.S. military departments, the need for recruiting and developing engineers has been noted (Castelli, 2011). Thus, there is an overall need in the U.S. for identifying factors that contribute to the recruitment and retention of future engineers. Vocational psychology research can assist in studying personal and environmental factors that facilitate or hinder the development and success of college students considering an engineering degree and career. Doing so can be of benefit at the personal, social, and institutional level of society in the U.S.

Engineering College Students

The demand for more professionals in STEM has extended over the years to a call for increasing the number of college students graduating with a STEM degree (President's Council of Advisors on Science & Technology, 2012). Within engineering, demand is understood to rely on an increasingly diverse talent pool that attends to the need for increasing and diversifying the engineering workforce in the U.S. (Chubin, May, & Babco, 2005). Calls to increase the number of engineering students have drawn attention to underrepresented students (President's Council of Advisors on Science & Technology, 2012), which includes first-generation college students (Martin, Miller, & Simmons, 2014). First-generation college students (FGCS) are an untapped increasing student population (Inkelas, Daver, Vogt, & Leonard, 2007; Terenzini et al., 1995) that can help address the need for more engineering professionals in the U.S. (Verdin & Godwin, 2018). Increasing the number of underrepresented groups in engineering is crucial to building a competitive engineering workforce (National Academy of Engineering, 2011). Understanding factors that increase interest, access, and persistence in engineering among FGCS is important for addressing their underrepresentation and capitalizing on this pool of potential future engineers. Identifying retention strategies for FGCS in engineering benefits the students themselves and the needs of both the engineering sector and the overall U.S. workforce (e.g., a more diverse and skilled workforce), which further serves to help keep the U.S. globally competitive and economically strong.

STEM degrees include mathematics and statistics, computer and information science, biological and biomedical sciences, engineering and engineering technologies, and physical sciences and science technologies (Musu-Gillette et al., 2017). Although there is a need to increase the number of college students pursuing engineering degrees, current barriers and attrition in STEM fields is of great concern (Espinoza, 2011), particularly for women and underrepresented racial/ethnic groups. Previous research shows that about 55% of those who start with a STEM college major do not persist in their goals to obtain a STEM degree (Chen, 2009). This is notably the case for women and individuals from underrepresented racial/ethnic groups (Espinoza, 2011; Griffith, 2010) who tend be a large portion of FGCS (Terenzini et al., 1995; Verdin & Goodwin, 2018). Latinx students and White female students, for instance, are substantially underrepresented in the engineering field and have among the highest attrition rates in undergraduate engineering programs (Musu-Gillette et al., 2017). In 2013-14, although women obtained about 57% of all bachelor's degrees, they received about 35% of STEM related bachelor's degrees compared to men at 65% (Musu-Gillette et al., 2017). Bachelor's degrees in STEM accounted for about 17% of all college degrees awarded, with Asian students accounting for percent 31% of those STEM degrees, followed by 17% for White students, 14% by Latinx students, and 11% by Black students (Musu-Gillette et al., 2017). More specifically, during the 2013-14 academic year, 64% of Latinx students obtaining a STEM degree were male and 67% of White students obtaining a STEM degree were male (Musu-Gillette et al., 2017).

Within engineering fields, FGCS face unique challenges such as not growing up having access to role models in engineering and developing their interest in engineering at a much later age compared to continuing generation college students (CGCS), as well as having to manage a difficult engineering course load compared to other FGCS not pursuing an engineering degree (Fernandez, Trenor, Zerda, & Cortes, 2008). Also, not being born in a college educated family disadvantages FGCS in that they have received less influences and resources related to engineering fields compared to CGCS (Martin, Miller, & Simmons, 2014). FGCS have also been found to be less prepared in advanced math and science courses compared to CGCS in college STEM programs (Chen & Soldner, 2013) which adds to potential barriers FGCS might face in obtaining an engineering degree. Despite some progress over the years, there is a continuing need to attend to expanding the preparation and presence of underrepresented groups in STEM fields (National Science Foundation, 2019).

First-Generation College Students

It is necessary to recognize that the attrition problem for FGCS goes beyond just trying to obtain an engineering degree. FGCS represent almost half of post-secondary students, but they are less likely to attend four-year universities and more likely to leave college without obtaining a degree compared to CGCS (Cataldi, Bennett, & Chen, 2018; Choy, 2001). FGCS who leave four-year institutions tend to do so before their second year in college (Choy, 2001), and if they do persist in obtaining a degree, FGCS tend to take more years on average to complete their undergraduate studies than their fellow CGCS (Cataldi et al., 2018). This can be partially due to FGCS tending to experience more challenges navigating the college environment (Collier & Morgan, 2007), such as being less prepared for the demands of a post-secondary education and facing more difficulties paying for school expenses (Pascarella, Pierson, Wolniak, & Terenzine, 2004). FGCS perceive more educational and career related barriers compared to CGCS (Raque-Bogdan & Lucas, 2016). Furthermore, the college adjustment experience is far more salient for FGCS because of their lack of college degree earning parents that can ease the transition into a university environment (Davis, 2010; Inkelas et al., 2007). Although FGCS may feel a sense of pride in being the first in their family to go to college, they can also perceive this identity as a contributing factor to social marginalization by CGCS given that they tend to report feeling misunderstood and disconnected from the CGCS population at large (DeRosa & Dolby, 2014). Moreover, previous research indicates that FGCS face challenges in having limited social and cultural resources for successfully navigating post-secondary environments (Garriott & Nisle, 2018) which can be particularly problematic in selective fields such as engineering (Martin, Miller, & Simmons, 2014). Overall, the literature provides a clear picture of challenges experienced by FGCS in and out of engineering majors. However, not much is known about how they negotiate these challenges and succeed in college, particularly in majors such as engineering.

College Level Support

College support systems have been found to have a positive impact on underrepresented groups such as FGCS. The first two years in college are known to be particularly important for recruiting and keeping students in STEM majors (President's Council of Advisors on Science and Technology, 2012). Social support strategies (e.g., peer-to peer support) have been suggested for retaining underrepresented students in STEM (National Academy of Engineering, 2011). These types of support programs have been found to increase persistence by influencing self-efficacy and professional identity in the STEM field of interest (Syed et al., 2018). Previous research suggests that environmental support systems in college can have positive effects on underrepresented college students in and out of STEM majors (Garriott, Hudyma, Keene, & Santiago 2015; Garriott & Nisle, 2018; Nix, Roberts, & Hughes, 2017; Inkelas et al., 2007; Soldner, Rowan-Kenyon, Kurotsuchi, Garvey, & Robbins, 2012; Szelényi, Denson, & Inkelas, 2013). The benefits from environmental support systems include fostering an essential sense of belonging and empowerment among FGCS in engineering (Verdin & Godwin, 2018). College student organizations focusing on STEM or engineering, for instance, have been found to generate positive outcomes among underrepresented students pursuing STEM careers (Mwaikinda & Aruguete, 2016; Revelo & Barber, 2018). This supports existing research noting that programs that promote social connectedness and opportunities for academic/scholarly activities might be the most effective in increasing persistence in STEM among college students

(Syed et al., 2018). However, there is a lack of research on the role of environmental factors and cognitive factors on students' academic and career development (Hurwitz et al., 2015).

Social Cognitive Career Theory

The present study uses Social Cognitive Career Theory (SCCT; Lent et al., 1994; 2000) to investigate the educational development process of FGCS pursuing engineering degrees and explores differences in the associations among variables between those who choose or choose not to participate in college STEM programs. The SCCT framework illustrates how personal and environmental factors interact to shape education/career choices. Under SCCT, choices and behaviors are influenced by cognitive-person variables (e.g., self-efficacy, personal goals, outcome expectations), environmental factors (e.g., support systems), and personal attributes (e.g., social identities such as gender and race/ethnicity) (Lent et al., 1994; 2000). Lent et al. (1994; 2000) suggest that contextual factors (e.g., supports and barriers) can moderate and directly influence educational/career related choices and behaviors.

Previous SCCT research has attended to cognitive-person variables among students pursuing a college degree in engineering (e.g., Flores et al., 2014; Lee, Flores, Navarro, & Kanagui-Muñoz, 2015; Lent et al., 2008) with other studies extending their focus to contextual factors (e.g., Garriott, Flores, & Martens, 2013; Garriott, Navarro, & Flores, 2017; Lent et al., 2014; Soldner, Rowan-Kenyon, Inkelas, & Robbins, 2012; Szelenyi, Denson, & Inkelas, 2013). Findings among these latter studies have illustrated a relationship between environmental supports and intended persistence that is mediated by self-efficacy and outcome expectations (Lent et al. 2013), as well as a relationship between social supports and goals that is mediated by self-efficacy and interests (Garriott et al. 2013). One study found a positive relationship between actual contextual support systems (e.g., university living learning communities) and social-cognitive variables (e.g., self-efficacy and outcome expectations) among women in STEM (Szelenyi et al., 2013).

Previous studies have recommended that future SCCT research continue to increase attention to contextual factors (e.g., supports) particularly among under-represented students in STEM (Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Garriott et al., 2013; Lent et al., 2013). These future research recommendations have extended to examining participation in actual environmental supports (e.g., student clubs) among FGCS (Garriott et al., 2013; Garriott, Hudyma, Keene, & Santiago, 2015). Directing SCCT research with students in engineering towards contextual factors can help shed light on possible areas of intervention related to retention and persistence. The current study builds on previous SCCT research focusing on cognitive-person and contextual factors by not only testing SCCT proposition and focusing on engineering students and FGCS, but by also extending the examination to students who participate or do not participate in STEM related programs in college.

Lent and colleagues (1994, 2000) indicate that SCCT can help us understand how choice behavior is influenced by contextual factors (e.g., supports). They suggest the importance of attending to contextual factors that facilitate career choice and development. Lent et al. (2000) note that research on contextual supports can complement scholarship attending to barriers. A recommendation by Lent et al. (2000) is for exploring how immediate sources of supports and barriers interrelate to influence career choice behavior. They highlight previous research (Lent et al., 1998) showing that social support systems (e.g., parents, faculty, peers, etc.) influence academic performance and choices related to college and career options. Thus, the current study takes on the goal of examining the influence of college level contextual support systems (e.g., engineering clubs) on FGCS pursuing a degree in engineering.

Purpose of the Study

The goal of the study was to use the SCCT framework (Lent et al., 1994, 2000) to examine the effects of proximal support systems on FGCS majoring in engineering. In particular, the present study tested an SCCT-based model to examine the effects of self-efficacy, outcome expectations, goals (i.e., intentions to persist), and actions (i.e., actual persistence) among White and Latinx FGCS in engineering who participate or do not participate in STEM related programs in college. The study's goal was to investigate a base model where engineering self-efficacy has an effect on outcome expectations, and self-efficacy and outcome expectations have an effect on actions through goals. A multiple group path analysis was generated based on participation in college STEM programs. The present study's focus on in-college STEM program participation answers Lent et al.'s (2000) call to differentiate between proximal and distal aspects of the environment and examine how certain "ecological structures facilitate or impede individual's career choice behavior" (p. 48). Lent el al. (2000) also indicate that the study of proximal influences can help offer insights with implications for developing interventions. Moreover, Lent et al. (2000) note that attention to supports systems over barriers honors the long-standing values of the counseling psychology field. Overall, the present study adds to the limited SCCT research on the impact of proximal support factors (e.g., participation in college STEM programs) on FGCS pursuing an engineering degree.

Chapter 2

Literature Review

This study intends to use Social Cognitive Career Theory (SCCT; Lent et al., 1994; Lent et al., 2000) to examine a model of engineering persistence intentions and actual persistence among FGCS. Specifically, the model includes cognitive-person variables (i.e., engineering self-efficacy, outcome expectations, goals, and actions) and a proximal contextual variable(i.e., college STEM program participation). The study will explore model variance across students based on college STEM program participation and nonparticipation. This chapter will discuss background information in regard to FGCS both within engineering and in college in general, followed by a review of in-college support systems, the SCCT framework, and a discussion of the objectives of the present study.

First-Generation College Students

A review of the literature generates variations in how FGCS status is defined. For instance, according to the U.S. Department of Education (2007), FGCS are "students who enrolled in a post-secondary education and whose parents do not have any postsecondary experience" (p. 3). However, researchers have underlined the need to expand the definition to students' whose parents have obtained some post-secondary education but not a 4-year college degree, referencing the unsuccessful parental attempt at getting a bachelor's degree, social/cultural factors influencing this outcome (e.g., socioeconomic status), as well as this broader definition encompassing common criteria used by college admissions officers (Davis, 2010; McCarron & Inkelas, 2006; Tate et al., 2015). Previous research illustrates meaningful differences in the college experience (e.g., attending less selective institutions and more likely to be enrolled part-time) between students with parents with no post-secondary experience, some post-secondary experience, at least one parent with a bachelor's degree, and two parents with a bachelor's degree (Pascarella, Pierson, Wolniak, & Terenzini, 2004). Therefore, this study will adopt the broader definition in which FGCS are students who do not have a parent who has graduated from a 4-year college/university.

FGCS represent almost half of post-secondary students, but they are less likely to attend four-year institutions and more likely to leave college without obtaining a degree compared to CGCS (Choy, 2001). FGCS who leave four-year institutions tend to do so before their second year in college (Choy, 2001). Previous research notes that FGCS tend to face unique challenges (e.g., limited economic, social, and cultural capital) that impact their college experience (Garriott & Nisle, 2018). For instance, some FGCS can feel socially disconnected from other college students because of social class differences (e.g., FGCS from low-income backgrounds) (DeRosa & Solby, 2014). Additionally, FGCS can experience more challenges, such as difficulties in navigating college culture (Collier & Morgan, 2007), being less prepared for college and facing more difficulties paying for school expenses (Pascarella, Pierson, Wolniak, & Terenzini, 2004). Thus, this contributes to FGCS' lower matriculation and persistence rates in four-year colleges. FGCS also tend to perceive more educational and career barriers and are less likely to reach those goals compared to CGCS (McCarron & Inkelas, 2006; Raque-Bogdan & Lucas, 2016).

FGCS are a disadvantaged college student population in that their parents have little to no experience in post-secondary education, which creates difficulties adjusting and navigating college compared to CGCS (Davis, 2010; Inkelas et al., 2007; Fernandez, Trenor, Zerda, & Cortes, 2008). Thus, the transition and college success process benefits students who have a family history of already navigating and completing a post-secondary education. A 2012 report on FGCS noted that only 24% of Latinx students have a parent who had obtained an associate degree or higher compared to 67% of Asians, 58% of Whites, and 33% of African Americans (Santiago et al., 2015). Further, FGCS are a unique social group in that they are not only defined by their parents' level of education but also by their diverse make up of separate marginalized social identities such as race/ethnicity and socioeconomic status (Garriott, 2019; Garriott & Nisle, 2017; Tarenzini et al. 1995; Verdin & Godwin, 2018; Ward, Siegel, & Davenport, 2012). Collectively, it is apparent that there is a connection between intersecting social identities (e.g., race/ethnicity, social class, FGCS status, etc.), post-secondary education attainment, and vocational outcomes in the U.S. Thus, it is imperative to consider the role of social representation in the college to career pipeline when examining promoters and barriers to building a diverse and robust engineering workforce.

Representation in Engineering

Engineering tends to be predominantly White and Asian men (Yoder, 2016), which is not representative of the U.S. population at large (Humes, Jones, & Ramirez, 2011). Black, Latinx, and Native Americans, as well as women across all racial/ethnic backgrounds are underrepresented in engineering (Byars-Winston, Branchaw, Pfund, Leverett, & Newton, 2015; Verdin & Goodwin, 2015). As previously noted, the gender disparity is large among White (67% male) and Latinx (64% male) populations (Musu-Gillette et al., 2017). For other racial/ethnic groups, the gap is narrower but still meaningfully large. For instance, among African Americans, the gender split is 56% male and 44% female, and among Asian students, the gender split is 60% male and 40% female (Musu-Gillette et al., 2017). Overall, the various underrepresented social identities that embody FGCS make this student group particularly unique and important for studying underrepresented college students pursuing engineering degrees. As stated before, the engineering field will benefit from utilizing a diverse portion of the U.S. population. However, access and utilization of underrepresented groups is conditional on members from these groups persisting in obtaining their college degree in engineering.

Barriers in STEM/Engineering among FGCS

Although FGCS can help meet the demand for more professionals in engineering, they face meaningful post-secondary level barriers. In addition to challenges previously noted for the general FGCS population, barriers specific to FGCS pursuing a STEM degree have been noted (e.g., less preparation in advanced math and science courses) (Chen & Soldner, 2013). FGCS in engineering, for instance, have been found to experience unique challenges that include not having access to role models in engineering, not learning about a possible career in engineering until late in their secondary education, as well as having to manage a difficult engineering course load compared to FGCS not majoring in a STEM related field (Fernandez, Trenor, Zerda, & Cortes, 2008). An understanding of factors that increase interest, access, and persistence in engineering among FGCS is important for addressing their underrepresentation and capitalizing on this pool of potential future engineers. Collectively, the literature provides a clear picture of challenges experienced by FGCS. However, not much is known about how they negotiate these challenges and succeed in college, particularly in majors such as engineering.

College Experiences and Trajectories for FGCS

A recent study by Garriott and Nisle (2018) examined stress, coping, and perceived academic goal progress among FGCS and CGCS. Using a transtheoretical model of stress and coping (Lazarus & Folkman, 1984), these researchers examined associations between: 1) stress and various sources of support, 2) perceived academic goal progress and coping resources, and 3) stress, sources of support, and perceived academic goal progress. The sample for this study consisted of 363 FGCS and 325 CGCS. In terms of gender, 499 were female and 182 were male.

It was a predominantly White sample (79.2%), and included students across all class levels (i.e., freshmen-seniors). There was also a large representation of various college majors. Using moderation analyses, findings indicated that stress was significantly related to institutional supports for only FGCS. Specifically, stress was negatively related with perceived academic goal progress among FGCS with access to support (e.g., teachers, mentors, etc.). Institutional supports explained the relation between stress and perceived academic goal progress for FGCS but not CGCS. Interestingly, friends and family supports did not explain the relation between stress and perceived academic goal progress for either FGCS or CGCS. The authors noted that results from this study reinforce advocacy for resources to support FGCS. Thus, an investigation of existing contextual sources of support (e.g., a college STEM programs) is important for guiding future development and improvement of support programs that aim to have positive academic and vocational effects on underrepresented students.

A previous study by Garriott, Hudyma, Keene, and Santiago (2015) tested the SCCT model of well-being (Lent, 2004) to predict academic and life satisfaction of FGCS and CGCS. Garriott et al. (2015) emphasized that there is a lack of research investigating predictors of academic and life satisfaction for FGCS. They also highlighted the current understanding of how environmental supports (on and off campus) can be important to the success and well-being of FGCS. Their sample of 414 students consisted of 52% FGCS and 48% CGCS. The sample was predominantly female (77.3%) and White (80.4%), and represented students across all undergraduate class levels. Using structural equation modeling (SEM), findings indicated that for both FGCS and CGCS, environmental supports related with college self-efficacy, college outcome expectations, and academic satisfaction. Moreover, college self-efficacy related with academic progress, and college outcome expectations related with academic satisfaction. Tests of mediation suggested that self-efficacy mediated the relationship between environmental supports and academic progress, and that outcome expectations mediated the relationship between environmental supports and academic satisfaction. The authors noted that the association between environmental supports and self-efficacy aligns with a previous study, with a predominant White sample, that found a positive relationship between social-efficacy and environmental supports in college (Lent et al., 2005). Garriott et al. (2005) concluded that the social cognitive model of well-being (Lent, 2004) shows potential for examining academic and life satisfaction among FGCS. Particularly important, the authors stated that future research can examine actual environmental supports (e.g., student clubs) rather than perceived environmental supports for FGCS. Thus, further supporting the rationale for the present study. Additionally, the authors state that the model can be used to examine the effects of interventions on SCCT variables such as outcome expectations related to obtaining a college degree in engineering. Limitations noted from this study included a lack of students of color, particularly since FGCS are predominantly from diverse racial/ethnic groups.

Most recently, Verdin and Godwin (2018) investigated the experiences of Latina FGCS in engineering. Using a qualitative thematic analysis approach, semi-structured interviews with seven Latina FGCS in engineering illustrated that difficulty with a sense of belonging was critical for this group of students. It is important to note, however, that there was a theme of students referencing an engineering student support program within the department for underrepresented students as a key source of support and empowerment. The authors noted that this program helped participants develop academically and socially. This study underlined the necessity of support systems for underrepresented students with intersecting social identities (e.g., women of color) in undergraduate engineering programs. Findings from this qualitative study support the previously reported quantitative research results illustrating the positive associations between environmental supports and other SCCT variables (e.g., outcome expectations) (Garriott et al., 2015). Moreover, Verdin and Godwin (2018) also called for future research on support programs for FGCS. Therefore, future research attending to success among engineering students will benefit from focusing on the intersecting marginalized social identities among such students.

Gibbons and Borders (2010) used SCCT (Lent et al., 1994) to study college related expectations among prospective and non-prospective FGCS in middle school. The sample of 272 participants was 34.2% White, 30.5% Black, and 23.9% Latinx. Of the 109 middle school prospective FGCS in the sample, 58 were Latinx, 24 were Black, and 15 were White. Gibbons and Borders (2010) underlined that the high number of Latinx FGCS relative to the other racial/ethnic groups was consistent with previous studies. Using factorial analysis of variances (ANOVAs), findings indicated that prospective FGCS reported lower college-going self-efficacy, lower outcome expectations, lower parental support, higher perceived barriers to college, and a higher likelihood to lack role models and support for educational planning compared to non-prospective FGCS. Results also indicated a significant interaction effect where male prospective FGCS reported lower self-efficacy expectations than male non-prospective FGCS. Additionally, among prospective FGCS, the study found a negative relationship between self-efficacy and perceived barriers, a negative relationship between perceived barriers and positive outcome expectations, and a positive relationship between social support and positive outcome expectations. Furthermore, among prospective FGCS, path analyses illustrated perceived barriers having a direct effect on college-going self-efficacy and an indirect effect on college-going intentions through college-going self-efficacy. Parental support was also found to have a direct effect on college-going self-efficacy and college-going negative outcome expectations. Similar to perceived barriers, parental support had an indirect effect on college-going intentions through college-going self-efficacy. College going self-efficacy expectations had a direct effect on positive and negative outcome expectations. Another finding that is important for this proposed study was a direct relationship between school support and positive outcome expectations. Collectively, Gibbons and Borders (2010) note that their findings are important from a general developmental and career development perspective. They recommended that future research attend to FGCS when examining educational/career related self-efficacy and outcome expectations. They also underlined the importance of future SCCT research continuing to attend to positive and negative expectations, as well as noted a need for longitudinal studies with FGCS to identify differences throughout their academic experience.

A more recent study by Garriott et al. (2017) also used SCCT (Lent et al., 1994, 2000) to examine FGCS' persistent intentions in engineering. The sample of 130 participants consisted of 70% Latinx, 23.1% White, and 7% bi-or-multiracial FGCS across all undergraduate class levels. Data were collected at two time points that were a year apart. A path analysis found, for instance, that Time 1 (T1) parent support was positively related to Time 2 (T2) engineering related verbal persuasion and vicarious learning. Results also indicated that self-efficacy mediated the relationship between realistic/investigative-themed performance accomplishments and physiological arousal to persistence intentions. Further, self-efficacy and outcome expectations were found to be associated with engineering persistence intentions. Contrary to previous research (e.g., Garriott et al. 2015; Lent et al., 2005), a relationship between self-efficacy and outcome expectations was not statistically significant in this study. Garriott et al. (2017) recommended that future research, particularly through a longitudinal design, pay attention to the first-year experiences of FGCS given that non-persistence intentions tend to occur by the end of the first year in college.

A review of the literature highlights important background information about FGCS and the need for more engineering professionals. However, a growing, but still limited, literature exists about those factors that facilitate persistence and success among FGCS pursuing an engineering degree. As previously stated, attending to FGCS in engineering also extends to focusing on multiple underrepresented social identities (e.g., women, underrepresented racial/ethnic, and students from low-income backgrounds). Additionally, previous research notes the importance of identifying sources of support that foster FGCS success in obtaining an engineering degree (Garriott et al., 2017). The present study will investigate the impact that proximal contextual support systems (e.g., participation in STEM college programs) have on SCCT variables among FGCS pursuing an engineering degree.

In-College Support Systems

An understanding of college level support systems that increase retention and persistence in engineering among FGCS is important for improving and/or developing more university-level programs that increase their access to and representation in engineering. Research on university-level programs have reported promising results for increasing the number of underrepresented groups in STEM. For instance, university-level programs targeting incoming STEM students have been found to increase STEM self-efficacy, sense of belonging, positive expectations in STEM careers, and lower intentions to leave STEM (Findley-Van & Pollenz, 2017; Soldner, Rowan-Kenyon, Inkelas, & Robbins, 2016; Szelenyi, Denson, & Inkelas, 2013).

Findley-Van and Pollenz (2017) evaluated a one-week pre-college STEM engagement program targeting retention of undergraduate students in STEM fields. The program took place one week before the start of the semester. The sample consisted of program and non-program participants who were incoming STEM students at the University of South Florida (USF). They found that program participants started their first semester in college with higher STEM self-efficacy, positive career expectancies, increased sense of belonging, and lower intentions to leave STEM compared to the control group. Furthermore, 91.7% of program participants stayed in their STEM major by the end of the first year in college compared to 87.2% of the control group. It is important to note that students had already been accepted into the university and had declared a STEM major. However, the 92% retention rate is noteworthy given that 55% of students of students starting with a STEM major do not go on to obtain a STEM degree (Chen, 2009).

A study by Inkelas et al. (2007) examined the role of living-learning (L/L) programs (i.e., supportive dormitory living environments) in facilitating FGCS perceived academic and social transition to college. The sample consisted of 1,335 FGCS from 34 universities who participated in the National Study of Living-Learning Programs during Spring 2004. Results indicated that FGCS in the L/L programs reported more successful academic and social transition to college than FGCS who lived in traditional residence halls. The authors suggested that the findings support the recruitment of FGCS to L/L programs. The authors recommend that future research should study the benefits and limitations of such programs among a diverse sample. The current study aimed to attend to the impact of similar in-college support systems among culturally diverse FGCS.

Similar results to the previously mentioned have been found in other studies focusing on women in STEM majors. For example, Szelényi, Denson, and Inkelas (2013) examined the impact of L/L programs and other college experiences on professional outcome expectations among women in STEM majors. Their results indicated that participating in STEM L/L programs was related to overall professional outcome expectations, expectations to achieve career success, and expectations to combine a professional career with having a balanced personal life. Additionally, Soldner, Rowan-Kenyon, Kurotsuchi, Garvey, and Robbins (2012) found that STEM focused L/L programs provide a socially supportive residential environment that promote positive outcome expectations in STEM particularly for women. Nix, Roberts, and Hughes (2017) also examined the impact of STEM L/L communities on educational outcomes among female undergraduate students. Results indicated that participants were three times more likely to complete a physical sciences, engineering, mathematics, and computer science degree than non-participants.

Student organizations have also been found to produce positive outcomes among students majoring in STEM fields. For instance, Revelo and Barber (2018) investigated the role of a Latinx-oriented engineering student organization on identity and resistant capital development among its members. The study found that involvement in the organization generated collective support among group members (e.g., commitment to increasing the number of Latinx in engineering) and increased identification to the engineering field. Furthermore, Mwaikinda and Aruguete (2016) found that students at a Midwestern Historically Black University (HBCU) who attended at least one STEM student organization meeting during an academic year displayed higher academic and social support, higher confidence in navigating the college setting, and greater contact with faculty compared to students that did not attend any meeting during the year, with FGCS tending to benefit the most from participating. This resembles another study finding that women of color who persisted in STEM tended to join STEM-related student organizations, engage in research experience, and attended a college with a strong community of STEM students (Espinosa, 2011). Moreover, Washburn and Miller (2004) reported on an undergraduate student organization that focused on attracting more women to a university's technology program and reducing attrition from the program. They found that members of the organization actively discussed barriers that women face in classroom settings (e.g., outnumbered by males, being intimidated, lack of respect by male peers, lack of female professors) and implemented retention strategies (e.g., creating a living/learning center in the residence halls for women in the school of technology).

Baker (2008) explored the impact of extracurricular activities on academic success among African American and Latinx college students. For this study, the author used Ogbu's (1993) theory of oppositional culture (i.e., social-historical focused theory on academic performance among underrepresented racial/ethnic groups) and Tinto's (1993) theory of educational departure (i.e., factors influencing students not persisting in college). The sample consisted of 3,294 college students from a dataset from the National Longitudinal Survey of Freshman (NLSF). Results indicated that some student organizations had a positive impact on the academic performance of Black and Latinx students. In particular, political organizations were found to be most beneficial for academic performance among underrepresented racial/ethnic college students. This was attributed to the possible positive effects on self-esteem and general self-efficacy that such organizations provide. Overall, the multiple previously reported studies underline the value of the current proposed study's aim to examine the impact of participating in college STEM support programs among FGCS pursuing an engineering degree.

Social Cognitive Career Theory

Social Cognitive Career Theory (SCCT; Lent, Brown, & Hackett, 1994, 2000) is a vocational psychology framework commonly used to examine academic and career development processes among college students. Developed from Bandura's (1977, 1986) social cognitive theory, SCCT attends to cognitive-person (e.g., self-efficacy, outcome expectations, interests, and goals) and environmental variables (e.g., contextual supports and barriers) that influence academic and career development (Lent et al., 1994, 2000). SCCT suggests that academic and career development is influenced by prior and on-going experiences that shape self-efficacy, outcome expectations, and goals in an ever-changing relationship (Lent et al., 1994), with contextual factors (i.e., supports, barriers) proposed to influence choices and actions (Lent et al., 2000). However, there is a limited amount of SCCT research examining the propositions related to contextual factors. Thus, for the purpose of this study, the role of a contextual factor (i.e., participation in college STEM programs) on the academic and career development process of FGCS in engineering was examined using SCCT as the theoretical framework.

In SCCT, self-efficacy relates to a person's belief in successfully completing a task, which is different from general self-esteem (i.e., confidence in the self) in that it mediates if and how a behavior within a particular domain will be performed (Bandura, 1977; Lent, Brown, & Larkin 1986). Self-efficacy influences outcome expectations, interests, goals, and actions (Lent., 2000), and it is also influenced by contextual factors (e.g., environmental supports and barriers) (Inda et al., 2013; Lent, 2004; Lent., 2008). Self-efficacy can include a FGCS's belief in his or her ability to obtain a bachelor's degree in engineering. It can influence their academic and career goals, and their intentions to persist with their goals (Lent, Brown, & Larkin, 1984; Wright et al., 2013). Self-efficacy can also influence a person's decision to persist in the face of barriers (Lent et al., 1994). High college self-efficacy during the first semester of college has been found to be related to likelihood to persist in college (Wright et al., 2013). Previous research with potential FGCS noted that self-efficacy was significantly associated with positive outcome expectations and unrelated to negative outcome expectations (Gibbons & Borders, 2010). Research with engineering students has also found women reporting lower self-efficacy relative to men (Inda, Rodriguez, & Peńa, 2013). Furthermore, with engineering majors, engineering self-efficacy has been found to predict intentions to persist in engineering and academic success (Lee, Flores, Navarro, & Kanagui-Munoz, 2015; Lent et al., 1984). Therefore, if students believe in their capabilities, they are more likely to keep working on an objective, expect positive outcomes from doing that work, and eventually reap the benefits.

In SCCT, outcome expectations are the perceived consequences from engaging in or completing a given task. Both self-efficacy and outcome expectations have a direct and indirect influence on career choice goals and actions (Lent et al., 1994). Lent et al. (1994) also explain that behavioral actions are influenced by self-efficacy and outcome expectations, with either self-efficacy or outcome expectations suggested to play a major role depending on the objective. For example, a student might value the possible outcomes related to obtaining a degree in engineering but doubt his or her ability to successfully complete some of the coursework necessary for the degree. Similarly, the student might have a high belief in the ability to perform well in engineering courses, but might find some outcomes related to becoming an engineer unappealing (e.g., stressful career). Moreover, previous research has attended to and recommended for future studies to attend to both positive and negative outcome expectations (Gibbons & Borders, 2010; Lee, Flores, Navarro, & Suh, 2016). Examining the influence of perceived positive and negative aspects of achieving an engineering degree, for instance, can aid in identifying areas of intervention and potential promoters and/or barriers to retention.

Previous SCCT research has found some notable findings related to outcome expectations. For example, previous research on prospective FGCS has found positive outcome expectations relating to self-efficacy, contextual factors (e.g., supports and barriers), and academic goals (Gibbons & Borders, 2010). Garriott et al. (2013) found that positive outcome expectations were influenced by contextual supports, but not barriers, in a sample of prospective FGCS. With a sample of FGCS in engineering, Garriott et al. (2017) also found that positive outcome expectations related to engineering persistence intentions, but not self-efficacy. Byars-Winston et al. (2010), however, found that positive outcome expectations related to self-efficacy and interests among a sample of racial/ethnic college students in a science and engineering major. In a study with a sample of White and Black engineering students, Lent et al. (2013) found that persistence intentions were influenced by self-efficacy and positive outcome expectations. Navarro et al. (2019) also found a relationship from positive outcome expectations to intended persistence among Latinx engineering students. Furthermore, with a sample of White and Latinx students in engineering, Flores et al. (2014) found support for a SCCT model where positive outcome expectations had a reciprocal relationship with engineering self-efficacy and engineering interest. Their results also illustrated that engineering outcome expectations related to engineering goals and engineering academic satisfaction. Moreover, a study by Inda et. al (2013) found that positive outcome expectations related to academic goals for both male and female engineering students. Findings also indicated that perceived contextual supports and barriers had a direct effect on outcome expectations. No gender differences related to outcome expectations were found in this study.

In SCCT, interests are preferences and insouciances for certain career related activities (Lent et al., 1994). Self-efficacy and outcome expectations are predicted to influence interests which, in turn, are hypothesized to effect goals (Lent et al. 1994). This process is expected to be fluid up to young adulthood where interests start to become clearer and more established yet still open to further changes (Lent et al. 1994). In addition, aspects of the environment are also expected to influence interests, such as moderating the previously mentioned relationship between interests and goals (Lent et al., 2000). For instance, supports can facilitate and barriers can hinder the positive effects of interests on goals (Lent et al., 2000). This will be important to examine in relation to the impact of college STEM program participation among FGCS in engineering.

Existing studies with FGCS and/or engineering students highlight notable findings between interests and other SCCT variables. With FGCS, Garriott et al. (2013) found that interests had a direct effect on goals and that interests mediated the relationship between self-efficacy and goals among prospective FGCS. With engineering student samples, studies found a direct effect from self-efficacy to interest (Lent et al., 2003) and from interests to goals (Byars et al., 2010; Inda et al., 2013). Interests have also been found to mediate the relationship between self-efficacy and goals (Lent et al. 2003). Furthermore, Flores et al. (2014) found that engineering interests had bidirectional relationships with engineering self-efficacy and outcome expectations. However, they noted that there was no significant relationship from engineering interests to engineering goals which is in contrast to previously mentioned research with engineering students (e.g., Byars et al., 2010).

In SCCT, goals have to do with the coordination of behaviors towards a specific destination that is related to the task of interest (Lent et al., 1994; Olson, 2014). Goal-directed behaviors (e.g., exploring career possibilities in engineering), for instance, can increase the likelihood of people obtaining a desired outcome (e.g., securing an attractive job in engineering) (Lent & Brown, 2013). Previous research has found that goals are good predictors of persistence in engineering (Lent et al., 2003). In addition, goals help people sustain behaviors for long periods of time that will lead to a desired future outcome, even when external reinforcements are not immediately available (Lent et al., 1994).

A review of the literature provides noteworthy associations between goals and other SCCT variables. For example, SCCT research with engineering students has found relationships between goals and outcome expectations (Byars et al., 2010), as well as with self-efficacy and interests (Inda et al., 2013). Lent et al. (2003) found that goals mediated the relationship between self-efficacy and interests to persistence. Similarly, with a White and Latinx engineering student sample, Lee et al. (2015) found through path analyses that engineering self-efficacy had a direct effect on engineering goals which then had a direct effect with future persistence actions in engineering. Furthermore, Flores et al. (2014), found among a sample of White and Latinx college students in engineering significant paths from engineering outcome expectations and self-efficacy to engineering goals. Flores et al. (2014) noted a lack of a significant path from engineering interests to goals in this study. Moreover, SCCT research with prospective FGCS has found goals to be influenced by social supports through self-efficacy, as well as goals being influenced by self-efficacy through interests (Garriott et al., 2013). It is important to note that this latter study did not find a significant relationship from self-efficacy to goals (Garriott et al., 2013).

SCCT also underlines the importance of learning experiences and contextual factors in academic and career development (Lent et al., 1994). Educational and social learning experiences, which includes feedback from other people, can influence college success (Brown, et al., 2008). For example, FGCSs who grow up with positive math and science academic experience prior to college will likely have high self-efficacy and outcome expectations about their potential performance in their college level engineering courses. Lent et al. (2000)

described contextual factors as objective (e.g., financial resources), perceived (e.g., interpretation of certain events as supports or barriers), distal (e.g., background circumstances that influence career-related self-efficacy and outcome expectations), or proximal (e.g., experiences that influence career-related decision making). SCCT suggests that proximal contextual supports can influence behaviors towards goals (Lent et al., 2000), such as in pursuing a degree in engineering. Additionally, contextual factors shape the development of self-efficacy and outcome expectations (Lent et al., 1994). For instance, proximal contextual factors (e.g., barriers and supports) may influence how students perceive whether or not their efforts towards an engineering degree will pay off. In support of Lent et al. (1994), a meta-analysis by Byars-Winston, Diestelmann, Savoy, and Hoyt (2017) found that performance accomplishments were the highest of four classes of experiences influencing self-efficacy in both STEM and non-STEM fields. A more recent meta-analysis on SCCT studies in the STEM domain by Sheu et al., (2018) found that previous direct personal experiences and vicarious learning were two key factors predictive of self-efficacy and outcome expectations. The present study aimed to attend to proximal objective contextual supports by examining the influence of college STEM program participation on the relations among the SCCT variables with FGCS in engineering.

Previous SCCT studies with FGCS and/or engineering students have found important relationships between proximal contextual factors (e.g., support systems) and other social-cognitive variables. For example, Gibbons and Border's (2010) study with prospective FGCS found that college-going self-efficacy was directly and positively affected by perceived parental support, as well as directly and negatively influenced by perceived barriers. Social supports were also found to positively relate with positive outcome expectations. However, perceived barriers were positively related with negative outcome expectations and negatively related with positive outcome expectations. An effect from perceived barriers to college going intentions was mediated by college going self-efficacy. A recent similar study by Kantamneni et al. (2018) with prospective FGCS also found that contextual factors (e.g., parental support and perceptions of barriers) related with educational/vocational self-efficacy and educational/vocational outcome expectations. In addition, Garriott et al.'s (2013) study with FGCS found supports and barriers had a direct effect on goals. Their findings also showed that social supports, but not barriers, were associated with positive outcome expectations and goals through math/science self-efficacy. Notably, in this study, contextual factors (e.g., supports and barriers) did not moderate a relationship between interests and goals as proposed by SCCT (Lent et al., 2000). Furthermore, previous SCCT research with engineering majors found contextual supports and barriers were associated with self-efficacy, outcome expectations, and goals (Inda et al., 2013). Lent et al. (2003) reported a bi-directional effect between supports and barriers with each having a significant path to engineering self-efficacy among engineering majors. Proximal contextual factors (e.g., supports and barriers) were also found to have an indirect effect on interests, goals, and persistence through engineering self-efficacy. Similar, Lent et al. (2013) reported that environmental supports and resources had a direct effect on self-efficacy and outcome expectations, an indirect effect on interests and intended persistence through self-efficacy and outcome expectations. Byars et al. (2010) also found that perceived campus climate (i.e., contextual factor) had an effect on academic goals through self-efficacy among college STEM majors. Finally, using a sample of White and Latinx students in engineering, Navarro et al. (2019) found that perceived engineering supports related positively with engineering self-efficacy, outcome expectations, and intentions to persist in engineering. Based on their findings, the authors recommended that future studies examine the relationship between engineering supports and intentions to persist in engineering

Fouad and Santana (2017) noted that most SCCT research on underrepresented groups has focused on pre-college choices, with recent trends towards focusing on choices in college and in the workplace. They indicated that SCCT is appealing for examining gender differences in STEM because of the model's attention to person inputs and contextual factors. Additionally, they reported that previous research has found support for SCCT models with underrepresented groups pursuing STEM majors (e.g., predicting choice of major in engineering and intentions to persist in engineering). They highlight that previous research has found the relationship between a low sense of belonging and low research self-efficacy and academic persistence among underrepresented racial/ethnic students majoring in engineering. They also review the positive impact of in-college support programs (e.g., living learning programs) on underrepresented groups (e.g., higher self-efficacy, outcome expectation, etc.). Fouad and Santana (2007) call for future research to explore whether some contextual supports (e.g., mentoring) are more beneficial for some student groups over others. Recent research has also underlined the importance of attending to contextual factors, such in making sure to consider culturally relevant factors when providing career counseling to social/cultural underrepresented student groups pursuing STEM careers (Rottinghaus, Falk, & Park, 2018).

Using SCCT, Raque-Bogdan and Lucas (2016) found no differences between FGCS and CGCS in regard to college self-efficacy, college outcome expectations, coping self-efficacy and career aspirations. They noted that exploring socio-economic status might indicate meaningful differences among individuals from different class groups. Although financial resources cannot be rejected as important factors, access to cultural/social capital (e.g., first in the family versus one of many in the family to go into engineering) might also show meaningful differences. Understanding contextual factors that contribute to these similarities or differences is important for identifying sources for support for FGCS which includes those pursuing engineering degrees.

Recently, Lent et al. (2018) conducted a meta-analytic path analysis of the SCCT base model (Lent et al., 1994, 2000) with STEM related studies from 1983 to 2013. They found that the SCCT base model had a good model-data fit across gender and racial/ethnic groups. Findings also included a stronger negative relationship between supports and barriers among women compared to men and a stronger negative relationship between supports and barriers among underrepresented racial/ethnic groups compared to majority racial/ethnic groups. These findings offer practical suggestions for interventions, such as promoting social supports and strategies for coping with anticipated barriers, that can improve engagement in STEM fields among underrepresented groups (Lent et al., 2018). Moreover, Lent et al. (2018) recommend extending the study of the SCCT base model to actions, such as actual persistence in obtaining an undergraduate degree in engineering.

Present Study

A review of the literature provides great insight about the needs of FGCS, the needs of the engineering field, and the potential benefits of contextual sources of support for underrepresented students pursuing engineering degrees. For instance, FGCSs can find themselves not knowing how to develop themselves towards their career of choice (Tate et al., 2015). Support systems such as STEM college programs can help with this process. Previous research suggests that FCGS obtain social and cultural capital through extracurricular activities where they interact with other peers possessing various sources of knowledge for successfully navigating college (Pascarella & Terenzini, 2005). Prior research has also called for an investigation of sources of support for FGCS (Gibbons, Rhinehart, & Hardin, 2019). Researchers noted support for using SCCT with FGCS because of its focus on individual and contextual factors (Garriott, Flores, & Martens, 2013). Attention to contextual variables have also been recommended in other SCCT studies (Flores et al., 2014). However, limited information about the use of SCCT on FGCS has been noted (Raque-Bogdan & Lucas, 2016). There remains a dearth of research specifically investigating the impact of STEM college program participation among FGCS in engineering. In particular, although SCCT research on perceptions of contextual supports exist, there does not appear much scholarship on actual contextual sources for support, such as in-college STEM program participation. Therefore, the present study aimed to examine the impact of in-college STEM program participation on SCCT variables among FGCS pursuing an engineering degree.

Specifically, the present study tested the SCCT base model (Lent et al., 1994, 2000, 2005) to identify the best model fit with FGCS in engineering and explore the effects of participating in STEM college programs (i.e., proximal contextual supports) with best fitting model. The base model included hypothesized relations among self-efficacy, negative outcome expectations, goals and actions as proposed by SCCT (see Figure 1). Structural equation modeling (SEM) was used to test the fit of the hypothesized model with FGCS pursuing an engineering degree. Once the model with the best fit was found, multigroup analyses between in-college STEM program participants and non-participants was conducted.

The following hypotheses were proposed (See Figures 1 through 5):

Hypothesis 1: The data will be a good fit to the base SCCT model.

Hypothesis 1a: Self-efficacy will have a direct effect on outcome expectations.

Hypothesis 1b: Goals will mediate the relationship between self-efficacy and actions.

Hypothesis 1c: Goals will mediate the relationship between outcome expectations and actions.

Hypothesis 2: Paths within the best fitting model will differ based on college STEM program participation. Specifically, the relations among the variables will be stronger for students who have participated in STEM programs than students who have not participated in STEM programs.

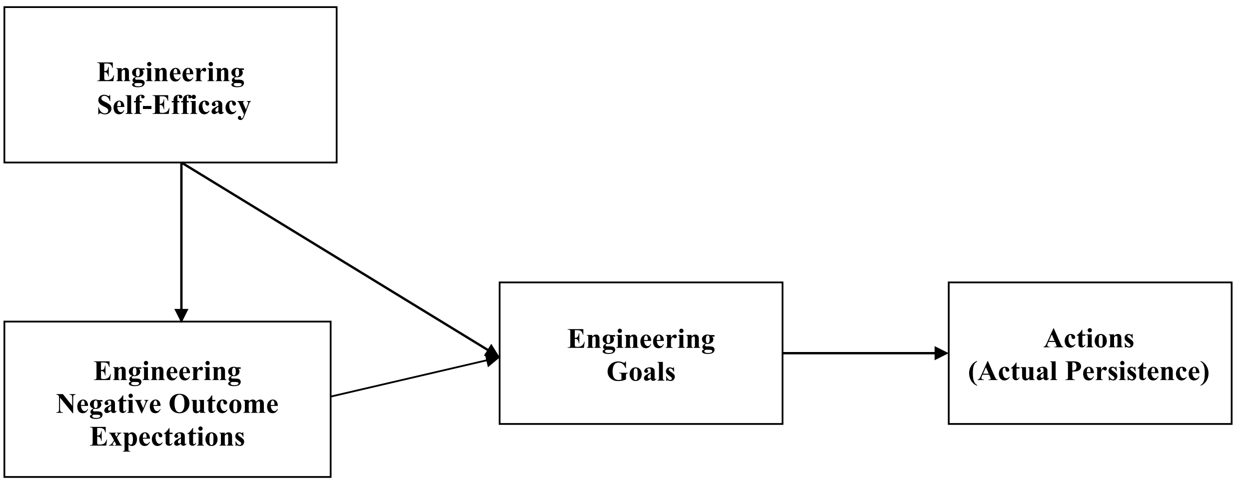

Figure 1. Proposed Model

Chapter 3

Method

The study examined through Social Cognitive Career Theory (SCCT; Lent et al. 1994, 2000, 2001, 2003, 2005) the influence of proximal contextual factors (i.e., involvement in college STEM programs) on person-cognitive variables (i.e., engineering self-efficacy, negative outcome expectations, goals, and actions) among FGCS pursuing a degree in engineering. Specifically, guided by SCCT (Lent et al., 1994, 2000), the study aimed to examine a base model with hypothesized person-cognitive variables (i.e., engineering, self-efficacy, negative outcome expectations, goals, and actions). The base model included hypothesized relations where self-efficacy has an effect on negative outcome expectations and both self-efficacy and negative outcome expectations have an effect on actions through goals. This was followed by a multigroup analyses based on participation in college STEM program participation. The study also explored temporal relationships from T1 to T2 variables while controlling for associations across time. The present study aimed to bring attention to college level proximal contextual factors that facilitate academic/career choice and development among FGCS pursuing an engineering degree. This chapter outlines the student population sample, the measures, and the data collection strategies, as well as the plan of analysis.

Procedures

Data for the present study came from a larger longitudinal study on engineering students that collected data from a quantitative (Qualtrics) survey from Spring 2015 and Spring 2016 across 11 universities in the U.S. Six of universities were Hispanic serving institutions (HSIs) located in the Southwest, Southeast, or Westcoast region of the U.S. The other five universities were Predominantly White Institutions (PWIs) located in the Northeast, Southeast, Southwest, or

Westcoast region of the U.S. Collectively, participants came from university campuses medium to large in size. The data collection was part of a larger longitudinal study aimed at understanding the underrepresentation, persistence, and satisfaction of women and Latinx college students in engineering. The larger study was funded through a grant from the National Science Foundation (NSF). Researchers across four universities in the U.S. facilitated the development and implementation of the study. All procedures were managed according to guidelines established by each university's Institutional Review Boards (IRB). Participants were recruited to complete the Qualtrics survey through classroom presentations, flyers, and email announcements. Participants were eligible to receive a $20 electronic Amazon gift card for their participation during T1 and $40 during T2. Survey incentives increased for each year the participant completed a survey. As indicated above, this study focused on data collected from T1 to T2. The larger study is important in that it is an on-going longitudinal project attending to social-cognitive experiences of under-represented groups in engineering college programs.

Participants

Participants were 473 first-generation college students, with 347 (73.4%) identifying as Latinx and 126 (26.6%) identifying as White. Of these participants, 297 (62.8%) identified as male and 176 (37.2%) identified as female. In terms of class standing, 84 (17.8%) were first year, 105 (22.2%) were sophomores, 164 (34.7%) were juniors, and 120 (25.3%) were seniors. Age ranged from 18-52 years ($M = 21.78$, $SD = 3.90$), where 51 (11%) participants were twenty-six years of age or older, and 1 participant did not provide their age. In terms of engineering majors, the following was reported: 110 (23.3%) in mechanical engineering, 87 (18.4%) in computer engineering, 85 (18.0%) in electrical engineering, 73 (15.4%) in civil engineering, 28 (5.9%) in biomedical engineering, 27 (5.7%) in chemical engineering, 23 (4.9%) in industrial engineering, 14 (3.0%) in aerospace engineering, 4 (0.8%) in architectural engineering, 3 (0.6%) in engineering management, 3 (0.6%) in metallurgical and materials engineering, 2 (0.4%) in geosystems engineering and hydrogeology, 2 (0.4%) in materials science and engineering, 1 (0.2%) in manufacturing engineering, 1 (0.2%) in ocean engineering, and 10 (2.1%) did not report a specific engineering major. Among the sample, 245 (51.8%) reported participating in a STEM college program and 228 (48.2%) reported not participating in an in-college STEM program. In alignment with previous research (Davis, 2010; McCarron & Inkelas, 2006; Tate et al., 2015), participants in the present study are considered FGCS if neither of their parents have 4-year college degree.

Measures

Demographic variables. Participants completed a demographic questionnaire regarding age, gender, race/ethnicity, undergraduate class standing, engineering major, involvement in STEM college programs, name of the STEM college program, parents' highest educational level, and current status in engineering (e.g., undergraduate engineering student).

In-College STEM program participation. To assess for in-college STEM program participation, participants answered yes or no to an item asking, "During your undergraduate career, did you participate in any programs that focused on STEM? Examples include NMSU-MARC (Minority Access to Research Centers), HS-STEM summer Internship Program, and ACCESS-Achieving Competence in Computing, Engineering, and Space Science."

Engineering self-efficacy. Lent et al.'s (2005) engineering self-efficacy (ESE) scale is a 4-item measurement that assesses confidence in one's ability to succeed in an engineering major (e.g., "excel in your engineering major over the next semester"). Participants respond to items using a 10-point Likert type scale, ranging from 0 (*no confidence*) to 9 (*complete confidence*).

Scores are averaged across all four items, with high scores reflecting high levels of engineering self-efficacy. Previous research has provided validity and reliability support of the scale's scores with engineering students identifying as Black, Latina/o, and White (e.g., Flores et al., 2014; Lent et al., 2005; Lent et al., 2007). Engineering self-efficacy scores have been found to be positively correlated with engineering outcome expectations, interests, goals, and academic satisfaction among a sample of undergraduate engineering students (Flores et al. 2014). Previous studies have reported coefficient alphas ranging from .88 to .92 for this measure among undergraduate engineering students (Flores et al., 2014; Garriott et al., 2017; Lent et al., 2005; Lent et al., 2007; Navarro et al., 2014; Navarro et al., 2019). The coefficient alphas for the ESE scale in the present sample were .92 at T1 and .77 at T2.

Negative outcome expectations - Engineering. The Negative Outcomes Expectations Scale – Engineering (NOES-E; Lee et al., 2016) is a 21-item measure of various negative outcomes that a participant might expect from obtaining a college degree in engineering (e.g., "high levels of stress due to a demanding work environment that affects my home life''). Participants respond to items using a 10-point Likert scale, ranging from 0 (*strongly disagree*) to 9 (*strongly agree*). The NOES-E is composed of four subscales: cultural-related stressors, personal life and work balance, job characteristics, and social costs. Construct validity of the NOES-E was supported through a positive correlation with a measure of engineering barriers and negative correlations with measures of engineering self-efficacy, academic satisfaction, intended persistence, supports, and positive outcome expectations (Lee et al., 2016). Previous research with Latina/o and White engineering students reported a Cronbach's alpha of .94 for scores from this measure (Lee et al., 2016). The coefficient alphas for the NOES-E in the present sample were .90 at T1 and .89 at T2.

Engineering goals/persistence intentions. Engineering goals were measured using Lent et al.'s (2003) Engineering Persistence Intentions (EPI) scale, which is a 4-item measure of academic persistence intentions in engineering (e.g., "I am fully committed to getting my college degree in engineering"). Participants respond to items using a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). High scores indicate strong intentions to pursue an engineering degree. In previous research, the EPI scores were positively correlated with engineering self-efficacy, interests, positive outcome expectations, and actual verified persistence (Lent et al., 2003; Lent et al., 2013), and previous research with samples of engineering students have yielded internal consistency values ranging from .72 to .95 (Garriott et al., 2017; Lent et al., 2003, 2005, 2008; Navarro et al., 2014; Navarro et al., 2019). The coefficient alphas for the EPI scale in the present sample were .92 at T1 and .94 at T2.

Engineering persistence (Actions). Persistence in engineering was assessed through participants' response to an item inquiring about their current status in engineering. Participants selected one of eight options that best fit their current status in engineering. (e.g., "graduated with a bachelor's degree in engineering and employed"). For the purposes of this study, persistence was scored among participants who reported that they remain enrolled in their engineering major or have graduated from college. For instance, persistence was designated for participants who reported graduating with a bachelor's degree in engineering regardless, for instance, if they reported now being employed in/out of engineering or being in graduate school, whereas non-persistence was designated for participants reporting graduating without a bachelor's degree in engineering. Moreover, persistence/actions were assessed at T2 only in this study.

Research Design/ Statistical Analysis Plan

This study examined whether data from FGCS pursuing an engineering degree at one of eleven universities across the U.S. will fit the hypothesized model related to SCCT (Lent et al., 1994, 2001, 2003, 2005). Data will be screened for missing values before conducting the primary analyses. Missing data will be addressed through literature recommended procedures. For instance, cases will be removed where there is more than 20% of missing data based on previous literature recommendations (Peng, Harwell, Liou, & Ehman, 2006; Schlomer, Bauman, & Card, 2010). Additionally, Little's Missing Completely at Random Test (MCART) will be conducted to determine if data is missing at random (Schlomer et al., 2010). If appropriate, the expectation-maximization (EM) method with single imputation, for instance, can be used to replace missing values as recommended in the literature (Schlomer et al., 2010). This will be followed by an examination of multivariate assumptions (Tabachnick & Fidell, 2007; Weston & Gore, 2006), which will include examining skewness, and kurtosis.

The study used structural equation modeling (SEM) to test the fit of hypothesized model with FGCS and to examine if participating in college STEM programs influences the relations among variables within the proposed models. Appropriate fit indices were used to examine the fit of the hypothesized models. These included the comparative fit index (CFI), the root of means square (RMSEA), and the standardized root mean square residual (SRMR). Appropriate cut off values were based on previous research guidelines (e.g., Hu & Bentler, 1999; Kline, 2005). For instance, adequate fit to the data is determined when CFI $\geq .90$, RMSEA $\leq .10$, and SRMR values $\leq .08$, whereas excellent fit to the data is determined when the CFI $\geq .95$, RMSEA $\leq .08$, and SRMR values $\leq .05$ (Kline, 2005, Kline, 2016). This was followed by testing the significance of the paths among the variables as outlined by SCCT (Lent et al., 1994, 2000). To determine impact of in-college STEM program participation, multiple group path analysis with SEM was used to determine whether college STEM program participation influences relationships within the best fit model. A structural model was tested where college STEM program participation was not be allowed to vary on any of the model parameters. A significant chi-square statistic and other fit statistics would be indicative of differences between the groups and, thus, a moderating effect for college STEM program participation. If different, models based on in-college STEM program participation versus no-college STEM program participation would be compared to examine paths that differ between the groups.

Chapter 4

Results

Preliminary Analysis

Missing data screening and pattern of missingness were done using IBM SPSS Version 26. Total percentage of missing data was 28%. Little's MCAR test (Little, 1988) suggested that data could not be assumed to be missing completely at random (MCAR; $\chi^2 = 366.925$, $df = 290$, $p = .001$). Thus, data were either missing at random (MAR) or missing not at random (MNAR).

Significant MCAR warranted corrective steps through multiple imputation to prevent biased results (Rose & Frazer 2008). While it is impossible to determine whether data is MAR or MNAR, certain procedures for handling missing data can make the assumption that the missing data mechanism is MAR more plausible. Researchers recommend the use of auxiliary variables (i.e., variables in the dataset correlated or assumed to be associated with missingness that are added to the imputation model) which help meet MAR condition, in multiple imputation (MI) to address missing data and improve accuracy of results (Baraldi & Enders, 2010; Collins, Schafer, & Kam, 2001; Howard, Rhemtulla, & Little, 2015). Additionally, principal components analysis (PCA) is recommended to help identify a suitable set of auxiliary variables, that contain most of the variance among all possible auxiliary variables, to inform the missing data process (Howard et al., 2015).

Given that the previous steps help meet MAR (Howard et al., 2015), a Multiple Imputation with Chained Equation (MICE) is recommended for extracting the auxiliary components (Azur, Stuart, Frangakis, & Leaf, 2011). MICE is a procedure where a series of regression models replace continuous or binary missing values for all variables with imputed values, one iteration (or "cycle") per variable, followed by repeated cycles (5-10 is sufficient) of updated imputations, creating various datasets that result in a final completed imputed dataset (Azur et al., 2011). In the present study, 10 repeated iterations of MICE were used to extract the auxiliary components (21 linear and 104 nonlinear), with 100 datasets imputed and combined to generate the final dataset. PCA and MICE procedures were done with R statistical software (version 3.5.1), using package PcAux (Lang, Curtis, & Bontempo, 2017). Primary analyses were also conducted using R statistical software.

Normality of data was examined by assessing skewness and kurtosis. Those values are recommended to be between -2 and 2 (Pituch & Stevens, 2016). This examination indicated that T1 goals was negatively skewed at -2.46 and with a kurtosis value of 7.79. All other variables were between -2 and 2 for skewness and kurtosis. Nevertheless, subsequent analyses were done with estimation that can be used with both normal and non-normally distributed data, as well as with both continuous and binary data which are part of present study (e.g., binary actions variable). Table 1 represent means, standard deviations, ranges, skewness, and kurtosis values for variables in this study. Table 2 shows this information separated by FGCS who participated or did not participate in a STEM college programs.

Primary Analyses

Due to the actions outcome variable being categorical, diagonally weighted least squares (DWLS) estimation was used to fit a CFA model. DWLS is suitable to use with data that is categorial and non-normally distributed and outperforms maximum likelihood estimators with such data (Li, 2016a; Li, 2016b; Muthen, duToit, & Spisic, 1997). Robust corrections, via weighted least squares mean and variance (WLSMV), was utilized to increase confidence in estimates of model fit (Savalei, 2014). Models were specified using standardized latent variable method. For the single-indicator factor, (i.e., actions), residual variance was constrained to zero and the factor loading was constrained to one in order to estimate latent variance.

A CFA model including each latent variable was estimated. However, this resulted in identification issues. In order to develop an acceptable measurement, the subscales of the NOE measure were parceled as this measure contained the largest number of indicators. Parceling (e.g., averaging item scores into a larger indicator of a latent construct) can be a suitable way to improve model fit when a measure for construct includes large number of indicators (Little, 2013). Additionally, parceling is acceptable with previously validated scales, particularly when the study focuses on relationships at the latent level (Little, Cunningham, Shahar, & Widaman, 2002). Given that the NOE subscales are previously validated and showed acceptable reliability, four parcels were created for each of the subscales. The result of the measurement model (χ^2 = 525.35, $p < .05$, robust CFI =.991; robust TLI = .989; robust RMSEA = .050 [90% CI = .04, .05]; SRMR = .051) showed good fit according to Hu and Bentler's (1999) cutoffs. The measurement model also exhibited strong factor loadings ($\lambda > .500$), and expected latent covariances, all of which were significant.

A series of models were examined to identify the best fitting model for the sample of this study. Autoregressive partial mediation model was used due to its appropriateness for longitudinal data with two time points (Cole & Maxwell, 2003; Maxwell, Cole, & Mitchell, 2011). Cole and Maxwell's (2003) recommendations for half-longitudinal designs were followed. This was important for analyzing the present study's two-time points design, but it did reduce the number of paths that could be examined (i.e., self-efficacy to goals). Furthermore, due to non-normal and binary data, DWLS estimator was also used for primary analyses. Additionally, likelihood ratio tests (LRT), as recommended by Satorra (2000), were used to compare models. Moreover, analyses included dropping goals item 4 (i.e., "I am fully committed to getting my college degree in engineering") because of low variance in response to this item, resulting in nonsignificant negative loading (Kolenikov & Bollen, 2012).

Table 3 shows the base models that were run and compared to identify the best fitting model. This included running model 1 (M1) with all T1 items correlated to their respective T2 items for each measure, followed by model 2 (M2) with correlation of T1 to T2 self-efficacy items constrained to zero (uncorrelated), followed by model (M3) with correlation of T1 and T2 goals items constrained to zero (uncorrelated), followed by model 4 (M4) where T1 to T2 self-efficacy items and goals items were constrained to zero (uncorrelated), followed by model 5 (M5) which was a time-invariant version (controlling for change in time among variables) of the best fitting model (M3) relative to the preceding comparisons (M5: DWLS $\chi^2 = 328$, $p < .001$, robust CFI =.94; robust TLI = .93; robust RMSEA = .03 [90% CI = .025, .040]. As noted previously, fit indices and LRT were used to identify the best fitting model. Significant chi squares are sensitive to sample size and, therefore, not considered suitable for identifying best fitting model (Kenny & McCoach, 2003).

After finding the best fitting baseline model, multiple groups SEM was utilized to examine the extend that group 1 (participating in college STEM program) and group 2 (not participating in college STEM program) were invariant across their factor loadings, path coefficients, and threshold parameter. Invariance was determined by systematically constrained models and the use of LRTs. Significant value would indicate that the more constrained model results in significantly worse model fit and is thus rejected. A nonsignificant LRT would suggest that the more constrained model did not result in a significant decrease in model fit and it is, thus, concluded that invariance holds.

Multiple groups analysis took a four-step approach of examining a configural invariance model (M6), metric invariance model (M7), path invariance model (M8), and threshold invariance model (M9). Table 4 shows all four group invariance models tested. In the configural invariance model, model specifications were the same as the best fitting base model, but both groups were allowed to have their coefficients freely load across groups. This model showed good fit, showing that the groups share the same hypothesized form (same factor structure across groups). Thus, since configural invariance was supported, analyses proceeded to testing the metric invariance model where both groups were constrained to have the same factor loadings across groups. The metric invariance model (the more constrained model) was compared to the configural invariance model (the less constrained model). The LRT was non-significant (p = .42) and, thus, invariant factor loadings were concluded. Constraining the loadings across groups did not significantly affect model fit. Since the metric invariance model was supported, analyses proceeded to testing the path invariance model where the constraints of metric invariance model were included in addition to the regression coefficients being forced to the same across groups. The non-significant LRT (p = .31) indicated that regression coefficients were invariant across groups. Since the path invariance model was supported, analyses proceeded to testing the threshold invariance model, where the same constraints of the path invariance model were induced in addition to constraining the threshold parameter of the action variable to be the same across groups. The significant LRT (p = .03) suggested that constraining this parameter resulted in worse model fit which indicated that this parameter in non-invariant. This implied differences between the groups (participating vs not participating in college STEM program). The non-invariant threshold parameter for the actions/persistence variable indicates that the groups need different level of goals for persistence to take place (from 0 to 1 since the actions variable is binary). Results indicate that group 1 (participating in college STEM program) requires lower levels of goals to persist compared to group 2 (not participating in college STEM program). Table 5 shows thresholds parameter estimates for group 1 and group 2.

The following relates to coefficients, variance explained, and final path model. Table 6 includes baseline model path coefficients for the full sample. Table 7 includes invariant path model coefficients for group 1 and group 2. Unstandardized coefficients are the same because they were constrained and did not result in fit that was significant. Standardized coefficients differ across groups because no constraints were imposed the variance of the variables across the groups. The final model accounted for 22% in self-efficacy, 11% in negative outcome expectations, 3% in goals, and 55% in persistence (actions). Moreover, Figure 2 presents factor loadings and path coefficients for final model. As noted earlier, half-longitudinal design led to a reduction in paths that were examined (i.e., self-efficacy to goals

Table 1
Variable Means, Standard Deviations, Range, Skewness, Kurtosis, and Correlations for full sample (*n*= 473)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. T1 SE	-													
2. T1 Goals	0.30**	-												
3. T1 NOE Total	-0.27**	-0.26**	-											
4. T1 NOE CRS	-0.26**	-0.24**	0.90**	-										
5. T1 NOE PLWB	-0.19**	-0.17**	0.82**	0.63**	-									
6. T1 NOE JC	-0.26**	-0.22**	0.81**	0.65**	0.54**	-								
7. T1 NOE SC	-0.20**	-0.26**	0.87**	0.72**	0.62**	0.59**	-							
8. T2 SE	0.35**	0.18**	-0.16**	-0.13**	-0.14**	-0.10*	-0.16**	-						
9. T2 Goals	0.02	0.09*	-0.15**	-0.11**	-0.11*	-0.10*	-0.17**	0.35**	-					
10. T2 NOE Total	-0.22**	-0.11*	0.28**	0.28**	0.21**	0.22**	0.22**	-0.31**	-0.35**	-				
11. T2 NOE CRS	-0.21**	-0.11*	0.22**	0.29**	0.14**	0.16**	0.16**	-0.26**	-0.22**	0.87**	-			
12. T2 NOE PLWB	-0.18**	-0.08	0.24**	0.23**	0.23**	0.18**	0.18**	-0.18**	-0.09*	0.78**	0.60**	-		
13. T2 NOE JC	-0.23**	-0.11*	0.22**	0.21**	0.16**	0.26**	0.13**	-0.26**	-0.25**	0.80**	0.60**	0.54**	-	
14. T2 NOE SC	-0.11*	-0.07	0.22**	0.20**	0.15**	0.14**	0.25**	-0.30**	-0.54**	0.81**	0.60**	0.46**	0.52**	-
Mean	7.91	4.63	4.67	4.64	5.09	4.97	4.01	7.40	3.60	4.43	4.25	4.71	4.89	3.89
SD	1.74	0.67	1.38	1.59	1.64	1.57	1.69	2.20	1.61	1.40	1.63	1.65	1.62	1.96
Range	8.00	4.00	8.00	8.00	9.00	9.00	9.00	9.00	4.00	8.67	8.67	8.60	8.60	8.80
Skewness	-0.73	-2.46	0.35	0.24	0.16	0.27	0.85	-0.93	-0.65	-0.14	0.15	0.03	-0.14	0.20
Kurtosis	-0.13	7.79	0.42	-0.24	-0.02	-0.09	0.54	0.30	-1.26	0.48	-0.03	0.19	0.09	-0.87

Note. SE = self-efficacy, NOE = negative outcome expectations, CRS = cultural-related stressors, JC = job characteristics, PLWB = personal life and work balance, SC = social costs

** Correlation is significant at the .01 level.

* Correlation is significant at the .05 level.

Table 2

Variable Means, Standard Deviations, Range, Skewness, and Kurtosis for **Group 1 and Group 2**

Variable	*M*	*SD*	Range	Skewness	Kurtosis
Group 1 (*N* = 245)					
T1 NOE CRS	4.68	1.53	8.00	0.17	-0.30
T1 NOE PLWB	5.17	1.58	9.00	0.15	0.20
T1 NOE JC	4.96	1.46	8.00	0.22	-0.15
T1 NOE SC	4.04	1.63	8.00	0.88	0.77
T1 NOE Total	4.71	1.28	8.00	0.27	0.75
T2 NOE CRS	4.35	1.64	7.67	0.17	-0.19
T2 NOE PLWB	4.85	1.60	8.60	0.07	0.31
T2 NOE JC	4.88	1.50	8.60	-0.06	0.24
T2 NOE SC	3.97	1.93	7.80	0.19	-0.87
T2 NOE Total	4.51	1.36	7.86	-0.06	0.42
T1 SE	7.99	1.72	8.00	-0.92	0.32
T2 SE	7.50	2.10	9.00	-0.82	-0.12
T1 Goals	4.71	0.60	4.00	-2.98	11.83
T2 Goals	3.69	1.61	4.00	-0.75	-1.15
Group 2 *(N = 228)*					
T1 NOE CRS	4.60	1.65	8.00	0.32	-0.27
T1 NOE PLWB	5.01	1.72	9.00	0.21	-0.28
T1 NOE JC	4.99	1.70	9.00	0.31	-0.23
T1 NOE SC	3.98	1.77	9.00	0.82	0.26
T1 NOE Total	4.64	1.48	8.00	0.43	0.06
T2 NOE CRS	4.15	1.63	8.67	0.13	0.05
T2 NOE PLWB	4.57	1.70	8.60	0.04	-0.01
T2 NOE JC	4.91	1.75	8.60	-0.21	-0.17
T2 NOE SC	3.81	2.00	8.80	0.23	-0.91
T2 NOE Total	4.35	1.45	8.67	-0.19	0.39
T1 SE	7.84	1.77	7.25	-0.53	-0.59
T2 SE	7.30	2.31	9.00	-0.99	0.43
T1 Goals	4.55	0.75	4.00	-2.03	5.11
T2 Goals	3.51	1.62	4.00	-0.55	-1.38

Note. Group 1 = Participated in college STEM program. Group 2 = Did not participate in college STEM program. SE = self-efficacy, NOE = negative outcome expectations, CRS = cultural-related stressors, JC = job characteristics, PLWB = personal life and work balance, SC = social costs

Table 3
Base Models

Model	$\chi 2$ (df)	Scaled $\chi 2$ (df)	Robust CFI	Robust TLI	Robust RMSEA [90% CI]	Model Comparison	$\Delta\chi 2$ (df)	p-value
M1	214.31 (206)	331.14*** (206)	0.93	0.91	0.04 [0.029, 0.043]	N/A	N/A	
M2	223.63 (210)	343.95*** (210)	0.92	0.91	0.04 [0.030, 0.044]	M1	33.75*** (4)	<. 001
M3	216.30 (213)	333.79*** (209)	0.93	0.92	0.04 [0.028, 0.043]	M1	4.49 (3)	.21
M4	230.42 (213)	351.39*** (213)	0.92	0.91	0.04 [0.030, 0.044]	M3	39.18*** (4)	<. 001
M5	227.58 (217)	328.00*** (217)	0.94	0.93	0.03 [0.025, 0.040]	M3	6.40 (8)	.60

Note. $N = 473$; Difference test is function of standard x2 statistics. $\Delta\chi 2$ = Likelihood ratio value.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 4
Group Invariance Models

Model	$\chi 2$ (df)	Scaled $\chi 2$ (df)	Robust CFI	Robust TLI	Robust RMSEA [90% CI]	Model Comparison	$\Delta\chi 2$ (df)	p-value
M6	336.14 (434)	527.52*** (434)	0.94	0.94	0.03 [0.02, 0.04]	N/A	N/A	
M7	350.19 (442)	533.38** (442)	0.95	0.93	0.04 [0.02, 0.04]	M6	8.8 (8)	.42
M8	390.81 (448)	531.14** (448)	0.95	0.94	0.04 [0.03, 0.04]	M7	7.13 (3)	.31
M9	395.68 (449)	534.78** (449)	0.95	0.94	0.04 [0.02, 0.04]	M8	4.87* (1)	< .05

Note. $N = 473$; In program = 245; Not in program = 228. Difference test is function of standard x2 statistics.
$\Delta\boldsymbol{\chi 2}$ = Likelihood ratio value.
* $p < .05$, ** $p < .01$, *** $p < .001$

Table 5
Threshold Parameter Estimates for Group 1 and Group 2

Variable	Estimate	SE	*p*-value
Group 1 (*N* = 245)			
Persistence	-0.965	0.095	< .001
Group 2 (N = 228)			
Persistence	-0.674	0.090	<. 001

Note. Group 1 = Participated in college STEM program. Group 2 = Did not participate in college STEM program.

Table 6
Base Model Path Coefficients

Effect	Coefficient	SE	Standardized
Self-Efficacy$_1$ → Self-Efficacy$_2$	0.55***	0.08	0.47
Negative Outcome Expectations$_1$ → Negative Outcome Expectations$_2$	0.22***	0.22	0.22
Engineering Goals$_1$ → Engineering Goals$_2$	0.20	0.20	0.09
Self-Efficacy$_1$ → Negative Outcome Expectations$_2$	-0.19***	0.05	-0.18
Negative Outcome Expectations$_1$ → Engineering Goals$_2$	-0.11	0.06	-0.11
Engineering Goals$_2$ →Persistence	0.52***	0.11	0.74

Note: Subscripts $_1$ and $_2$ = time point 1 and time point 2; "Persistence" is a time-invariant endogenous variable
* *p* <= .05. ** *p* <= .01. *** *p* <= .001

Table 7
Invariant Path Coefficients

Effect	Coefficient	SE	Standardized
Group 1			
Self-Efficacy$_1$ → Self-Efficacy$_2$	0.55***	0.08	0.51
Negative Outcome Expectations$_1$ → Negative Outcome Expectations$_2$	0.21***	0.05	0.21
Engineering Goals$_1$ → Engineering Goals$_2$	0.20	0.13	0.08
Self-Efficacy$_1$ → Negative Outcome Expectations$_2$	-0.21***	0.05	-0.21
Negative Outcome Expectations$_1$ → Engineering Goals$_2$	-0.10	0.06	-0.08
Engineering Goals$_2$ → Persistence	0.51***	0.10	0.73
Group 2			
Self-Efficacy$_1$ → Self-Efficacy$_2$	0.55***	0.08	0.43
Negative Outcome Expectations$_1$ → Negative Outcome Expectations$_2$	0.21***	0.05	0.22
Engineering Goals$_1$ → Engineering Goals$_2$	0.20	0.13	0.10
Self-Efficacy$_1$ → Negative Outcome Expectations$_2$	-0.21***	0.05	-0.19
Negative Outcome Expectations$_1$ → Engineering Goals$_2$	-0.10	0.06	-0.10
Engineering Goals$_2$ → Persistence	0.51***	0.10	0.74

Note: Subscripts $_1$ and $_2$ = time point 1 and time point 2; "Persistence" is a time-invariant endogenous variable
* *p* <= .05. ** *p* <= .01. *** *p* <= .001

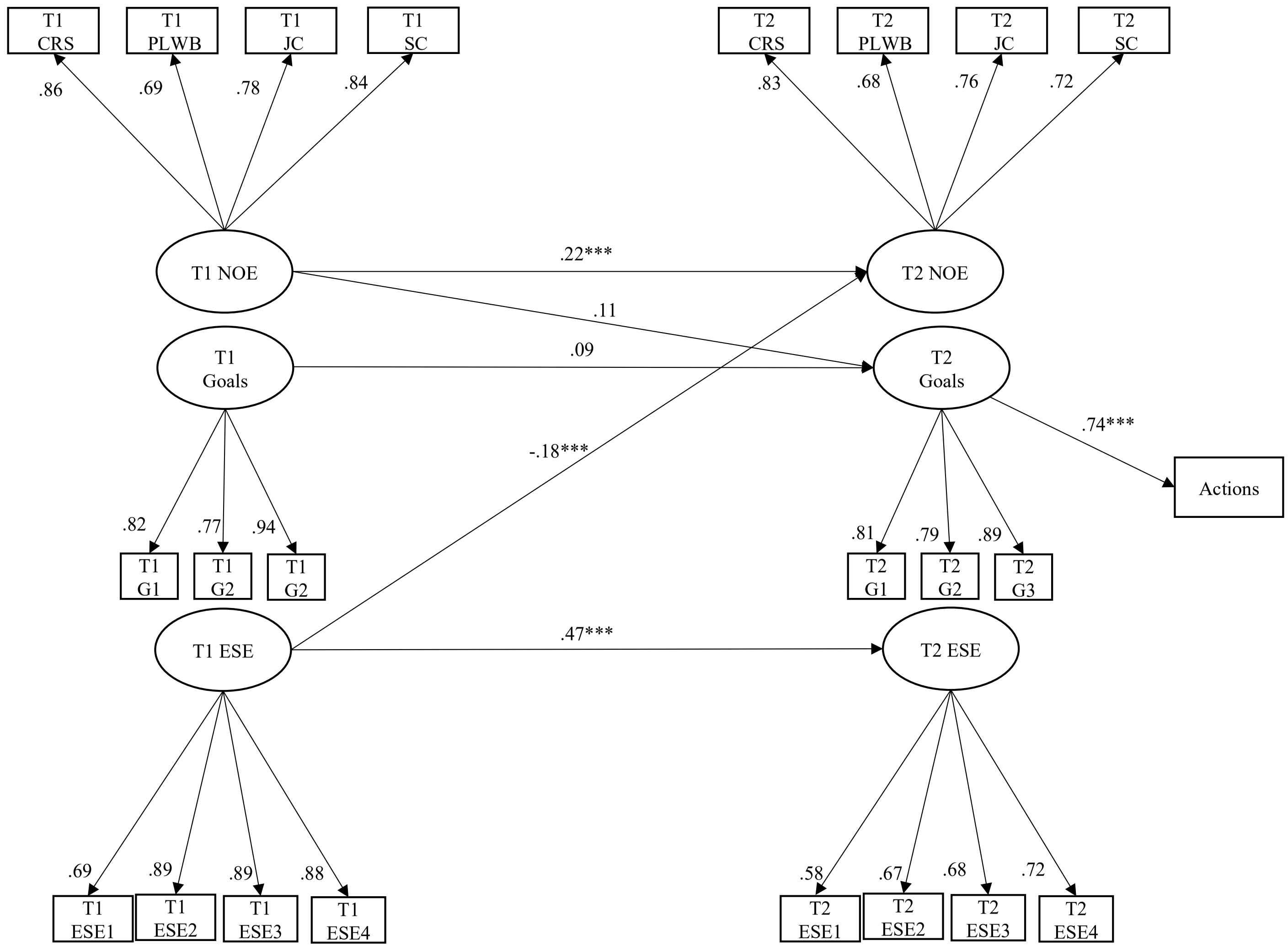

Figure 2. Final model
Note. SE = self-efficacy, NOE = negative outcome expectations, CRS = cultural-related stressors, JC = job characteristics, PLWB = personal life and work balance, SC = social costs, Actions = Persistence

Table 8
Frequencies of Persistence in Engineering based on Gender, Race/Ethnicity, Undergraduate Level, and College STEM Program Participation

Variable	Frequency	Percent
	Persistence	
Gender		
Female	135	77
Male	240	81
Race/Ethnicity		
Latinx	270	78
White	105	83
Undergraduate Level		
Freshman	64	76
Sophomore	85	81
Junior	132	81
Senior	94	78
Program Participation		
No	171	75
Yes	204	83

Note: N = 473. Female = 176, Male = 297, Latinx = 347, White = 126, Freshman = 84, Sophomore = 105, Junior = 164, Senior = 120, Participated in STEM Program = 245, and Did Not Participate in STEM Program = 228

Chapter 5

Discussion

The purpose of this study was to use the SCCT framework (Lent et al., 1994; Lent et al., 2000) to examine the effects of proximal support systems on FGCS's persisting in an engineering degree. Relationships among variables of the SCCT-based model were examined for FGCS's majoring in engineering. The study found a significant direct effect from Time 1 engineering self-efficacy to Time 2 engineering negative outcome expectations, Time 1 engineering self-efficacy to Time 2 engineering self-efficacy, Time 1 engineering negative outcome expectations to Time 2 engineering negative outcome expectations, and Time 2 engineering goals to actions (actual persistence). Time 1 engineering goals to Time 2 engineering goals was not significant. There were no differences in the configural invariance, metric invariance, and path invariant models between FGCS in engineering who participated or did not participate in college STEM programs. However, results indicated a group difference in the threshold invariance model, where FGCS in engineering who participated in college STEM programs needed lower levels of engineering goals to persists in engineering compared to FGCS in engineering who did not participate in college STEM programs.

This study responded to a call for more information on the use of SCCT with FGCS (Gibbons & Borders, 2010; Raque-Bogdan & Lucas, 2016), focusing on contextual factors (Garriott et al., 2013; Garriott et al., 2015; Gibbons et al., 2019; Flores et al., 2014; Lent et al., 2000), negative outcome expectations (Gibbons & Borders, 2010; Lee et al., 2016) and actual persistence (Lent et al., 2018). Lent et al. (2000) described contextual support systems as an understudied variable in the literature. Garriott et al. (2005) also recommended future research to examine actual environmental support systems over perceived sources of support among FGCS.

Thus, this study added to the existing SCCT literature by examining the impact of participation in college STEM programs on the relations among social cognitions, including self-efficacy, negative outcome expectations, and goals, and actual persistence (actions), among FGCS Latinx and White students pursuing an engineering degree across multiple universities in the U.S. (i.e., 6 HSIs and 5 PWIs). The present study contributes to the vocational psychology literature examining personal and environmental factors that can help facilitate the success of FGCS pursuing a degree in engineering. The following includes an in-depth review of the findings from the present study, implications for future practice and research, and limitations.

The results of the present study suggested that the data with the full sample of FGCS was a good fit to the SCCT-based model. Time 1 engineering self-efficacy was found to have a significant negative effect on Time 2 engineering negative outcomes expectations. This aligns with previous research showing an effect from self-efficacy to outcome expectations (Byars-Winston et al., 2010; Flores et al. 2014; Garriott et al., 2015; Gibbons & Borders, 2010; Lent et., 2000). In particular, Time 1 self-efficacy effects on Time 2 outcomes expectations have been highlighted in SCCT literature (Lent, Miller, Smith, Watford, Lim, & Hui, 2016). Also, particularly relevant to the current study, the present study's results align with previous research finding self-efficacy having a direct effect on negative outcome expectations among prospective FGCS (Gibbons & Borders, 2010). Further, other research has not found self-efficacy to have an effect on positive outcome expectations among FGCS pursuing an engineering degree (Garriott et al., 2017). Overall, however, most of the research thus far has focused on positive outcome expectations. More research on the effects of self-efficacy on negative outcome expectations is warranted.

The present study's finding indicated that decreases in engineering self-efficacy will likely result in higher negative outcome expectations among FGCS pursuing an engineering degree. This suggests that if FGCS are having low self-beliefs about their ability to succeed in an engineering major, their perceived outcomes from continuing in this field start looking unfavorable. The negative outcome expectations subscales for the present study included cultural-related stressors, personal life and work balance, job characteristics, and social costs. Therefore, a FGCS losing confidence in succeeding in an engineering major might also start to have concerning expectations about what they might expect in a future job in engineering, such as negative job characteristics (e.g., "feeling frustrated with challenging tasks").

The current study's findings on the impact of engineering self-efficacy on negative outcome expectations add to the existing literature that has predominantly examined the impact of self-efficacy on positive outcome expectations. The current findings imply that low-self-efficacy might not only impact positive outcome expectations, but also negative outcome expectations among FGCS pursuing an engineering degree. Collectively, this underlines the importance of interventions and training that aim to increase self-efficacy among FGCS in engineering. Doing so might also alleviate averse outcome expectations related to entering the professional world of engineering.

The present study results indicated that T1 negative outcome expectations did not have a significant effect on T2 goals. Thus, negative outcome expectations did not have the hypothesized impact on actions (persistence) via goals among this sample of FGCS pursuing engineering degrees. Lent et al. (1994) noted that outcome expectations have a direct effect on goals and an indirect effect on actions. Additionally, Byars et al. (2010) found that outcome expectations had a direct effect on goals among a sample of STEM college students. Similarly, other previous studies have found that outcome expectations have a direct effect on goals among engineering majors (Flores et al., 2014; Inda et al., 2013). However, the current study focused on negative outcome expectations rather than positive outcome expectations which has been studied more in previous research. Thus, further examination of the influence of negative outcome expectations, perhaps relative to positive outcome expectations, among FGCS in engineering is warranted.

It might be that there are different factors at play contributing to the present study findings with negative outcome expectations. SCCT indicates that positive outcome expectations, for instance, are likely to positively influence stronger goals in an area of interest (e.g., engineering) through an on-going reinforcing cycle, which then impacts performance (e.g., persistence) (Brown & Lent 2013). Therefore, it might be the case that negative outcome expectations by their very adverse nature do not carry the reinforcing effect on goals compared to positive outcome expectations. Similarly, it might be that negative outcome expectations have no effect on goals when there is high self-efficacy and/or high positive outcome expectations (pros outweigh the cons). This could possibly be the case in the current sample where high scores on goals were observed. Furthermore, SCCT underlines the role of educational and social learning experiences that can influence academic/career development (Brown et al., 2008; Lent et al., 1994) which might help explain the distinct finding with negative outcome expectations in the present study. Previous research has also found previous personal experiences and vicarious learning to predict outcome expectations (Sheu et al., 2018), which might also help explain the distinct finding with negative outcome expectations. It might be that distal contextual factors (e.g., lack of career role models growing up), for instance, are uniquely influencing FGCS in engineering. Overall, this underlines previous calls to further study negative outcome expectations variable (Gibbons & Borders, 2010; Lee et al., 2016).

The present study's findings show the important role of goals on actions (i.e., actual persistence in engineering). Time 2 goals had a significant positive effect on actions (actual persistence in engineering). This suggests that FGCS in engineering who endorse high levels of goals are more likely to persist in engineering. This aligns with SCCT's emphasis on goals having a positive impact on actions (Lent et al., 1994; Lent & Brown, 2013). Previous research has shown that goals are good predictors of persistence in engineering (Lee et al., 2015; Lent et al., 2003; Lent et al., 2016). For instance, Lent et al. (2013) found goals to be a strong predictor of persistence among a sample of undergraduate students enrolled in an introductory engineering class. Additionally, from an SCCT perspective (Lent & Brown, 2013; Lent et al., 1994), it can be said that FGCS from the present study sample are continuing along a positive reinforcing cycle of goals and actions process (e.g., previous successes in high school, getting into a four-year college, passing engineering related courses, etc.) that will likely positively influence their next engineering related goals (e.g., engineering related training/employment opportunities). Overall, the present study extends goals-actions findings from previously noted studies by also focusing on FGCS pursuing engineering degrees.

Lent et al. (2000) underlined the importance of attending to the role of proximal contextual influences, such as environmental support systems. Thus, a particularly important finding in the current study was that FGCS majoring in engineering who did not participate in college STEM programs needed higher levels of engineering goals to persist relative to those who did participate in college STEM programs. Interestingly, participating in college STEM programs seemed to offer some relief of needing high levels of goals to persist in engineering.

This corresponds with Lent et al. (2000)'s emphasis on the influence of proximal contextual factors on the goals to action relationship under SCCT, as well as their noted speculation that supportive environmental systems might help individuals with minority identities and experiences (e.g., FGCS) succeed even in light of meaningful barriers (e.g., not having the same level of social/cultural capital to navigate college as successfully as continuing generation college students). For FGCS not participating in college STEM programs, they might also not have other sources of support and, thus, need higher levels of goals to persist. An example of this might be the FGCS who commutes to college from home, thus, does not get the benefits of participating in a college STEM program, and therefore, is reliant on having higher engineering related goals to persist. It is well documented that FGCS tend to generally feel more socially and culturally disconnected from CGCS (Davis, 2010; DeRosa & Solby, 2014; Fernandez et al,, 2008; Inkelas et al., 2007). Verdin and Godwin (2018) found that Latinx FGCS built their sense of belonging and empowerment in engineering through a college support system. Moreover, Lent et al. (1994) noted that goals are sometimes described as "aspirations or daydreams" (p.85). For the present study, this might mean that such aspirations or dreams for FGCS might be more real when in an affirming environment, such as a college STEM program (e.g., engineering student club), and thus lowering the threshold of the effects of goals on persistence. Overall, this study answers Lent et al. (2000)'s call for more research that complements the larger set of previous studies focused on barriers to career choice and development.

SCCT proposes that contextual factors can influence the goals to actions relationship (Brown & Lent, 2013; Lent et al., 2000). More specifically, supportive environments (e.g., college STEM programs) can aid the goals to actions (persistence) process (Brown & Lent, 2013). The present study finds that participating in college STEM programs has a supportive influence on persistence via goals which aligns with that SCCT proposition. This also aligns with previous research underlining the potential for college programs to help with the retention of underrepresented students in STEM (Soldner et al, 2016; Washhburn & Miller, 2004). Additionally, SCCT indicates that goals help people sustain behaviors for extended periods of time that will lead to desired future outcomes even when external reinforcements are not immediately available (Lent et al., 1994). This is important for a student population such as FGCS who already face more barriers compared to CGCS (Collier & Morgan, 2007; Davis 2010; Fernandez et al., 2008; Inkelas et al., 2007; Pascarella et al., 2004; Raque-Bogdan & Lucas, 2016). Previous studies have noted the benefits that engineering student organizations, for example, can have on underrepresented groups, such as collective support, increased identification to the engineering field, and retention (Espinoza, 2011; Revelo & Barber, 2018 Washburn & Miller, 2004). Overall, the present study findings suggest that participating in college STEM programs might help FGCS majoring in engineering persist compared to those who do not participate in such programs. This is valuable information for supporting FGCS pursuing an engineering degree. As stated by Lent et al. (2000), such information on proximal support systems can help direct the development of intervention that aims to help facilitate academic and career success.

Practical Implications

Results from the present study offer suggestions for developing college level interventions that support FGCS in engineering. For example, the findings underscore the valuable role college STEM programs can have on FGCS students' goals to persistence trajectory in getting an engineering degree. Universities can further support existing, or develop new programs, that aim to increase self-efficacy, for instance. This can be done through the promotion of pre-college (e.g., summer before first fall semester), early (e.g., first-year), or throughout college (i.e., on-going support) learning experiences that work to affirm, validate, empower, and motivate FGCS to persist in engineering. Such interventions would align with SCCT framework of learning experiences having an effect on self-efficacy (Lent & Brown, 2013). Previous research studies underline that participating in college programs is particularly beneficial for women and other under-represented racial/ethnic minorities who make up a large portion of the FGCS population (Santiago et al., 2015).

The present study findings are also useful at a more individual level. University personnel working directly with FGCS can use the results to encourage their students to seek, or help connect them with, educational opportunities that work to build and sustain beliefs in doing well in engineering. This includes academic advisors, instructors, career counselors, mental health therapists, wellness center coordinators, resident assistants, and other university staff that often work with college students. For example, an academic advisor might suggest college STEM program participation to a FGCS in engineering who is on probation and sharing that a lack of social connection with peers is a key contributing barrier to their academic success. Moreover, present study findings can also be helpful to parties outside the college setting such as high school teachers, high school counselors, and other educators/mentors of graduating high school seniors, who can encourage their students, particularly those from under-represented backgrounds, to participate in college programs related to their field of interest. This would be particularly helpful for FGCS expressing concerns about their capabilities to succeed in a college engineering program.

Research Implications, Limitations, and Future Directions

The present study offers support for the use of SCCT with FGCS in engineering. For instance, findings highlighted an effect from self-efficacy to outcome expectations, from goals to actions, and the influence of proximal support systems in engineering persistence. The use of the negative outcome expectations scale is a valuable added variable to the SCCT literature on FGCS in engineering. This is particularly true given the challenges FGCS already face in navigating college in general compared to CGCS. Similarly, the use of an actual proximal contextual influence (college STEM program participation) offered a novel component to the existing literature. This is important for underlining the value of college level programs. Moreover, the use of actual persistence in engineering is also a pertinent component for measuring action-based outcomes. This is important for increasing retention and persistence of FGCS in engineering.

While the previously noted research components contribute to the existing literature, present study limitations should be noted. This is particularly important for informing the direction of future research. A meaningful limit to the current study was the use of a half-longitudinal design because of the presence of only two time points which reduced the number of paths to be examined (Cole & Maxwell, 2003). For instance, the hypothesis that goals would mediate relationship between self-efficacy and actions was not examined. Similarly, design/analyses complexity and limitations did not allow for examination of positive outcomes expectations which could have offered helpful comparative information with the negative outcome expectations measure. In addition, the present study used a definition of FGCS that was limited to students who reported that neither of their parents had obtained a 4-year college degree. This might be an issue for a student from a single parent households, for instance, where the student is not raised by, and thus does not get the CGCS benefits, from the parent who obtained the degree but is absent from their life. Furthermore, the present sample was predominantly Latinx FGCS. A large Latinx FGCS sample is important given the under-representation of Latinx students in engineering. However, this sample composition also limits generalizability to the general college student population and other racial/ethnic minority groups. Moreover, the present study included students from all undergraduate levels which could influence levels of persistence (e.g., first year vs. fourth year undergraduate students pursing engineering degrees). Examination of social cognitions over time or undergraduate class standing, such as self-efficacy, might offer results that help educators aim interventions at specific academic time points (e.g., end of first-year in college) that can generate the most benefits to their students. It might be the case that freshman to sophomore year engineering self-efficacy is meaningfully lowered compared to junior to senior year where students already have multiple years of persistence in their major. In this scenario, FGCS in the early stages of their engineering studies might be struggling with challenging pre-requisite courses. This difficult time period might open them up to seeking sources of support, such as engineering student clubs, where they can gain and utilize social and cultural capital in an affirming environment that might directly or indirectly boost their engineering self-efficacy. It is important for future research to examine, across multiple time points and across different times in the academic year (e.g., start, mid, or end of year), the influence of undergraduate class standing on social cognitions and persistence of FGCS pursuing an engineering degree. Finally, due to complexity and difficulties with design and analysis, group analyses based on gender, race/ethnicity, type of institution (PWI vs HSI) were left out from the present study, which could have offered more nuanced information about this sample of FGCS pursuing an engineering degree.

The present study offers various helpful recommendations for future research. For example, future studies can examine whether findings generalize to FGCS in non-engineering degrees, CGCS in engineering, and/or other under-represented groups in and out of engineering majors. Other areas that warrant future research investigation include accounting for other important variables such as gender, FGCS parent household/upbringing composition (e.g., being raised only by parent without a college degree) socio-economics status, type of institution attended (HSI versus PWI), high school GPA, college admission tests scores, and pre-college STEM program participation. Accounting for type of institution attended, for instance, can be helpful for identifying large societal level contextual factors that influence the experience of students with underrepresented/marginalized identities. Findings from such analyses can help researchers better identify sources of support for a diverse FGCS student population across various academic/career trajectories. Furthermore, future research would benefit from utilizing both positive and negative outcome expectations measures with FGCS pursuing engineering degrees. Attending to these variables can potentially generate more information to direct future research and practice. Moreover, particularly important, future studies are directed to use longitudinal designs with more than two time points due to the limits on the analyses this created in the present study. Such longitudinal research can offer a richer picture of how SCCT variables impact FGCS in engineering across time, particularly as they transition from high school to college and move from college into the workforce.

References

Azur, M. J., Stuart, E. A., Frangakis, C., & Leaf, P. J. (2011). Multiple imputation by chained equations: what is it and how does it work? *International journal of methods in psychiatric research*, *20*(1), 40-49.

Baker, C. (2008). Under-represented college students and extracurricular involvement: the effects of various student organizations on academic performance. *Social Psychology of Education*, *11*(3), 273.

Bandura, A. (1986). The Explanatory and Predictive Scope of Self-Efficacy Theory. *Journal of Social and Clinical Psychology, 4,* 3, 359-373.

Baraldi, Amanda N., and Craig K. Enders. 2010. "An Introduction to Modern Missing Data Analyses." *Journal of School Psychology* 48, 5-37.

Brown, S. D., Tramayne, S., Hoxha, D., Telander, K., Fan, X., & Lent, R. W. (2008). Social cognitive predictors of college students' academic performance and persistence: A meta-analytic path analysis. *Journal of Vocational Behavior*, *72*, 3, 298-308.

Brown, S. D., & Lent, R. W. (2013). *Career development and counseling. [electronic resource] : putting theory and research to work* (2nd ed.). Wiley.

Byars-Winston, A. M., Branchaw, J., Pfund, C., Leverett, P., & Newton, J. (2015). Culturally diverse under-graduate researchers' academic outcomes and perceptions of their research mentoring relationships. International Journal of Science Education, 37, 2533–2554.

Byars-Winston, A., Diestelmann, J., Hoyt, W. T., & Savoy, J. N.. (2017). Unique effects and moderators of effects of sources on self-efficacy: A model-based meta-analysis. *Journal of Counseling Psychology*, *64*(6), 645–658. https://doiorg.proxy.mul.missouri.edu/ 10.1037/cou0000219

Castelli, C. J. (2011). Report: Military services ‘struggle’ to staff systems engineering jobs. *Inside the Pentagon*, *27*(18), 1. Retrieved from: http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.insipent.27.18.02&site=eds-live&scope=site

Cataldi, E. F., Bennett, C. T., Chen, X., National Center for Education Statistics (ED), & RTI International. (2018). *First-generation students: College access, persistence, and postbachelor's Outcomes. Stats in brief. NCES 2018-421*. National Center for Education Statistics.

Chen, X. (2009). Students who study science, technology, engineering, and mathematics (STEM) in postsecondary education (NCES 2009-161). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

Chen, X. & Soldner, M. (2013). *STEM Attrition: College Students' Paths Into and Out of STEM Fields (NCES 2014-001)*. National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC. Retrieved from: https://nces.ed.gov/pubs2014/2014001rev.pdf

Choy, S. P. (2001). *Students whose parents did not go to college: Postsecondary access, persistence, and attainment* (NCES 2001-126). Washington, DC: U.S. Department of Education, National Center for Educational Statistics.

Chubin, D., May, G., & Babco, E. (2005). Diversifying the engineering workforce. Journal of Engineering Education, *94*(1), 73–86. Retrieved from http://search.ebscohost.com. proxy.mul.missouri.edu/login.aspx?direct=true&db=edswss&AN=000231266300008&site=eds-live&scope=site

Cole, D. A., & Maxwell, S. E. (2003). Testing mediational models with longitudinal data: questions and tips in the use of structural equation modeling. *Journal of Abnormal Psychology*, *112*(4), 558.

Collier, P. J., & Morgan, D. L. (2008). “Is that paper really due today?”: Differences in first-generation and traditional college students’ understandings of faculty expectations. *Higher Education New York Then Dordrecht Elsevier Publishing Company Then Kluwer Academic Publishers-, 55,* 4, 425-446.

Collins, L. M., Schafer, J. L., & Kam, C. M. (2001). A comparison of inclusive and restrictive strategies in modern missing data procedures. *Psychological Methods*, *6*(4), 330–351.

Davis, J. (2010). The first-generation student experience: implications for campus practice, and strategies for improving persistence and success. Sterling, Va: Stylus, 2010. Retrieved from: http://search.ebscohost.com.proxy.mul.missouri.edu/login.aspx?direct=true&db=cat04885a&AN=merlin.b7456162&site=eds-live&scope=site

DeRosa, Erin, & Dolby, Nadine. (2014). *“I don’t think the university knows me.”: Institutional culture and lower-income, first-generation college students*. (InterActions: UCLA Journal of Education and Information Studies.) eScholarship, University of California.

Espinosa, L. L. (2011). Pipelines and Pathways: Women of Color in Undergraduate STEM Majors and the College Experiences That Contribute to Persistence. *Harvard Educational Review, 81,* 2, 209-241.

Fayer, S., Lacey, A., & Watson, A. (2017). *BLS spotlight on statistics: STEM occupations - past, present, and future*. Washington, D.C.: U.S. Department of Labor, Bureau of Labor Statistics. Retrieved from: https://www.bls.gov/spotlight/2017/science-technology-engineering-and-mathematics-stem-occupations-past-present-and-future/pdf/science-technology-engineering-and-mathematics-stem-occupations-past-present-and-future.pdf

Fernandez, M. J., Trenor, J. M., Zerda, K. S., Cortes, C., & 38th ASEE/IEEE Frontiers in Education Conference, FIE 2008. (2008). First generation college students in engineering: A qualitative investigation of barriers to academic plans. *Proceedings - Frontiers in Education Conference, Fie.*

Findley-Van Nostrand, D., & Pollenz, R. S. (2017). Evaluating Psychosocial Mechanisms Underlying STEM Persistence in Undergraduates: Evidence of Impact from a Six-Day Pre-College Engagement STEM Academy Program. *CBE - Life Sciences Education*, *16*(2).

Flores, L. Y., Navarro, R. L., Lee, H. S., Addae, D. A., Gonzalez, R., Luna, L. L., … Mitchell, M. (2014). Academic satisfaction among Latino/a and White men and women engineering students. *Journal of Counseling Psychology*, *61*(1), 81–92.

Fouad, N. A., & Santana, M. C. (2017). SCCT and Underrepresented Populations in STEM Fields: Moving the Needle. *Journal of Career Assessment*, *25*(1), 24–39.

Garriott, P. O. (*in press*). A Critical Cultural Wealth Model of First-Generation and Economically Marginalized College Students' Academic and Career Development. *Journal of Career Development*.

Garriott, P. O., Flores, L. Y., & Martens, M. P. (2013). Predicting the math/science career goals of low-income prospective first-generation college students. *Journal of Counseling Psychology*, *60*(2), 200–209

Garriott, P. O., Hudyma, A., Keene, C., & Santiago, D. (2015). Social cognitive predictors of first- and non-first-generation college students' academic and life satisfaction. *Journal of Counseling Psychology*, *62*(2), 253–263.

Garriott, P. O., Navarro, R. L., & Flores, L. Y. (2017). First-Generation College Students' Persistence Intentions in Engineering Majors. *Journal of Career Assessment*, *25*(1), 93–106.

Garriott, P. O., & Nisle, S. (2018). Stress, coping, and perceived academic goal progress in first-generation college students: The role of institutional supports. *Journal of Diversity in Higher Education, 11,* 4, 436-450.

Gibbons, M. M., Rhinehart, A., & Hardin, E. (2019). How first-generation college students adjust to college. *Journal of College Student Retention: Research, Theory & Practice*, *20*(4), 488–510.

Gibbons, M. M., & Borders, L. D. (2010). Prospective First-Generation College Students: A Social-Cognitive Perspective. *Career Development Quarterly*, *58*(3), 194–208. https://doi.org/10.1177/2156759X1001300404

Griffith, A. L. (2010). Persistence of Women and Minorities in STEM Field Majors: Is It the School that Matters? Economics of Education Review, 29(6), 911–922.

Inda, M., Rodríguez, C., & Peña, J. V. (2013). Gender differences in applying social cognitive career theory in engineering students. *Journal of Vocational Behavior*, *83*(3), 346–355. https://doi-org.proxy.mul.missouri.edu/10.1016/j.jvb.2013.06.010

Inkelas, K. K., Daver, Z. E., Vogt, K. E., & Leonard, J. (2007). Living–Learning Programs and First-Generation College Students' Academic and Social Transition to College. *Research in Higher Education*, *48*(4), 403–434.

Howard, W.J., Rhemtulla, M., & Little, T. D. (2015) Using Principal Components as Auxiliary Variables in Missing Data Estimation. *Multivariate Behavioral Research, 50*(3), 285-299. doi: 10.1080/00273171.2014.999267

Humes, K.R., Jones N.A., & Ramirez R.R. (2011). Overview of race and Hispanic origin: 2010. 2010 Census Brief. Retrieved from: https://www.census.gov/prod/cen2010/briefs/c2010br-02.pdf

Kenny, D. A., & McCoach, D. B. (2003). Effect of the number of variables on measures of fit in structural equation modeling. *Structural Equation Modeling, 10*, 3, 333-351.

Kline, R. B. (2005). *Principles and practice of structural equation modeling* (2n ed.). New York, NY: Guilford Press.

Kline, R. B. (2016). *Principles and practice of structural equation modeling (*4th ed.). New York, NY: Guilford Press.

Kolenikov, S., & Bollen, K. A. (2012). Testing Negative Error Variances: Is a Heywood Case a Symptom of Misspecification? *Sociological Methods & Research*, *41*(1), 124–167.

Lang, K.M., Curtis, J., Botntempo D.E. (2017). PCAux Field Guide. Why Git Hub? Retrieved from: https://github.com/PcAuxPackage/PcAux/blob/master/documentation/PcAux_Field_Guide.pdf

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. New York, NY: Springer.

Lee, H-S., Flores, L. Y., Navarro, R. R., & Kanagui-Muñoz, M. (2015). A longitudinal test of social cognitive career theory's academic persistence model among Latino/a and white men and women engineering students. *Journal of Vocational Behavior, 88*, 95-103. doi:10.1016/j.jvb.2015.02.003

Lent, R. W. (1994). Toward a Unifying Social Cognitive Theory of Career and Academic Interest, Choice, and Performance. *Journal of Vocational Behavior, 45*, 1, 79-122.

Lent, R. W. (2004). Toward a unifying theoretical and practical perspective on well-being and psychosocial adjustment. *Journal of Counseling Psychology, 51,* 482–509. doi:10.1037/0022-0167.51.4.482

Lent, R. W., Brown, S. D., Brenner, B., Chopra, S. B., Davis, T., Talleyrand, R., & Suthakaran, V. (2001). The role of contextual supports and barriers in the choice of math/science educational options: A test of social cognitive hypotheses. *Journal of Counseling Psychology*, *48*(4), 474–483. https://doi-org.proxy.mul.missouri.edu/10.1037/0022-0167.48.4.474

Lent, R. W., Brown, S. D., & Hackett, G. (2000). Contextual Supports and Barriers to Career Choice: A Social Cognitive Analysis. *Journal of Counseling Psychology, 47*, 1, 36-49.

Lent, R. W., Lopez, J. A. M., Lopez, F. G., & Sheu, H.-B. (2008). Social cognitive career theory and the prediction of interests and choice goals in the computing disciplines. *Journal of Vocational Behavior*, *73*(1), 52–62. https://doi-org.proxy.mul.missouri.edu/10.1016/j.jvb.2008.01.002

Lent, R. W., Miller, M. J., Smith, P. E., Watford, B. A., Lim, R. H., & Hui, K. (2016). Social cognitive predictors of academic persistence and performance in engineering: Applicability across gender and race/ethnicity. *Journal of Vocational Behavior*, *94*, 79–88. https://doi-org.proxy.mul.missouri.edu/10.1016/j.jvb.2016.02.012

Lent, R. W., Singley, D., Sheu, H.-B., Gainor, K. A., Brenner, B. R., Treistman, D., & Ades, L.

(2005). Social cognitive predictors of domain and life satisfaction: Exploring the theoretical precursors of subjective well-being. *Journal of Counseling Psychology, 52,* 3, 429-442.

Lent, R. W., Singley, D., Sheu, H.-B., Schmidt, J. A., & Schmidt, L. C. (2007). Relation of Social-Cognitive Factors to Academic Satisfaction in Engineering Students. *Journal of Career Assessment*, *15*(1), 87–97. Retrieved from http://search.ebscohost.com.proxy.mul.missouri.edu/login.aspx?direct=true&db=eric&AN=EJ749252&site=eds-live&scope=site

Lent, R.W., Sheu,H-B., Miller, M.J., Cusick, M.E., Penn, L.T., Truong, N.N. (2018). Predictors of Science, Technology, Engineering, and Mathematics Choice Options: A Meta-Analytic Path Analysis of the Social-Cognitive Choice Model by Gender and Race/Ethnicity. *Journal of Counseling Psychology*, *65*(1), 17–35. https://doi-org.proxy.mul.missouri.edu/10.1037/cou0000243

Little T.D. (2013). *Longitudinal structural equation modeling.* New York: The Guilford Press.

Little, T. D., Cunningham, W. A., Shahar, G., & Widaman, K. F. (2002). To parcel or not to parcel: Exploring the question, weighing the merits. *Structural Equation Modeling, 9*(2), 151-173.

Little, R. J. A. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association, 83*, 1198-1202.

Li, C. H. (2016a). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior research methods*, *48*(3), 936-949.

Li, C. H. (2016b). The performance of ML, DWLS, and ULS estimation with robust corrections in structural equation models with ordinal variables. *Psychological methods*, *21*(3), 369.

Lopez, F. G., & Lent, R. W. (1992). Sources of mathematics self-efficacy in high school students. *Career Development Quarterly*, *41*(1), 3. https://doi-org.proxy.mul.missouri.edu/10.1002/j.2161-0045.1992.tb00350.x

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55.

Hurwitz, J., Bosworth, K., Deil-Amen, R., Rios-Aguilar, C., Hendricks, J., & Rubenstein-Avila, E. (2015). Students' perceptions of academic efficacy and school supports: A mismatch with school demographics. *Current Issues in Education*, *18*(3). Retrieved from https://cie.asu.edu/ojs/index.php/cieatasu/article/view/1388

Martin, J. P., Miller, M. K., & Simmons, D. R. (2014). Exploring the theoretical social capital "deficit'' of first-generation college students: Implications for engineering education. *International Journal of Engineering Education*, *30*(4), 822–836. Retrieved from http://search.ebscohost.com.proxy.mul.missouri.edu/login.aspx?direct=true&db=edswsc&AN=000347457200007&site=eds-live&scope=site

Maxwell, S. E., Cole, D. A., & Mitchell, M. A. (2011). Bias in Cross-Sectional Analyses of Longitudinal Mediation: Partial and Complete Mediation Under an Autoregressive Model. *Multivariate Behavioral Research*, *46*(5), 816–841.

McCarron, G. P., & Inkelas, K. K. (2006). The gap between educational aspirations and attainment for first-generation college students and the role of parental involvement. Journal of College Student Development, 47(5), 534–549.

Musu-Gillette, L., de Brey, C., McFarland, J., Hussar, W., Sonnenberg, W., and Wilkinson-

Flicker, S. (2017). *Status and trends in the education of racial and ethnic groups 2017* (NCES 2017-051). U.S. Department of Education, National Center for Education Statistics. Washington, DC. Retrieved from http://nces.ed.gov/pubsearch.

Muthén, B., du Toit, S.H.C., & Spisic, D. (1997). Robust inference using weighted least squares and quadratic estimating equations in latent variable modeling with categorical and continuous outcomes. Retrieved from: https://www.statmodel.com/download/Article_075.pdf

Mwaikinda, S. R., & Aruguete, M. S. (2016). The Efficacy of a Student Organization for STEM Students. *Journal of Stem Education: Innovations & Research, 17,* 3.

National Academy of Sciences (U.S.), Institute of Medicine (U.S.), & National Academy of Engineering. (2011). *Expanding underrepresented minority participating: America's science and technology talent at the crossroads*. Washington: National Academies Press. Retrieved from: http://search.ebscohost.com.proxy.mul.missouri.edu/ login.aspx?direct=true&db=cat04885a&AN=merlin.b8494244&site=eds-live&scope=site

National Center for Education Statistics, U.S., Department of Education (2017). In *Mobile digest of education statistics 2017*. Retrieved February 26, 2019, from the National Education Association Website: https://nces.ed.gov/programs/digest/d17/tables/dt17_322.30.asp?current=yes

National Science Board (2018). Science and Engineering Indicators 2018. NSB-2018-1. Alexandria, VA: National Science Foundation. Retrieved from: https://www.nsf.gov/statistics/indicators/.

National Science Foundation, National Center for Science and Engineering Statistics (2019).

Women, Minorities, and Persons with Disabilities in Science and Engineering: 2019. Special Report NSF 19-304. Alexandria, VA. Available at www.nsf.gov/statistics/wmpd/.

Navarro, R. L., Flores, L. Y., Legerski, J.-P., Brionez, J., May, S. F., Suh, H. N., … Jung, A.-K. (2019). Social cognitive predictors of engineering students' academic persistence intentions, satisfaction, and engagement. *Journal of Counseling Psychology*, *66*(2), 170–183. https://doi-org.proxy.mul.missouri.edu/10.1037/cou0000319.supp

Nix, S., Roberts, K. L., & Hughes, R. M. (2017). Female undergraduate stem persistence: A focus on the role of living and learning communities. *Journal of Women and Minorities in Science and Engineering*, *22*(4), 349–374.

Olson, J. S. (2014). Opportunities, obstacles, and options: first-generation college graduates and social cognitive career theory. *Journal of Career Development, 41*, 3, 199-217.

Pascarella, E. T., Pierson, C. T., Wolniak, G. C., & Terenzini, P. T. (2004). First-generation college students: Additional evidence on college experiences and outcomes. *The Journal of Higher Education*, 75, 3, 249-284.

Peng, C. Y. J., Harwell, M. Liou, S. M., & Ehman, L. H. (2006). Advances in missing data methods and implications for educational research. In S. Sawilowsky (Ed.)., *Real Data Analysis* (pp. 31-78). Greenwich, CT: Information Age Publishing, Inc.

Pituch, K. A., & Stevens, J. (2016). *Applied multivariate statistics for the social sciences: Analyses with SAS and IBM's SPSS*.

President's Council of Advisors on Science and Technology (PCAST). (2012). *Engage to Excel: Producing One Million Additional College Graduates with Degrees in Science, Technology, Engineering, and Mathematics*. Washington, DC.

Raque-Bogdan, T. L., & Lucas, M. S. (2016). Career aspirations and the First-generation student:

Unraveling the layers with social cognitive career theory. *Journal of College Student Development, 57,* 3, 248-262.

Redford, J., Hoyer, K.M., & Ralph, J. (2017). *First-generation and continuing-generation college students: A comparison of high school and postsecondary experiences.* Stats in Brief. U.S. Department of Education. Retrieved 26, 2019, from U.S. Department of Education Website: https://nces.ed.gov/pubs2018/2018009.pdf

Revelo, R. A., & Baber, L. D. (2018). Engineering Resistors: Engineering Latina/o Students and Emerging Resistant Capital. *Journal of Hispanic Higher Education, 17,* 3, 249-269.

Rose, R. A., & Fraser, M. W. (2008). A simplified framework for using multiple imputation in social work research. *Social Work Research*, 32, 171–178. doi:10.1093/swr/32.3.171

Rottinghaus, P. J., Falk, N. A., & Park, C. J. (2018). Career Assessment and Counseling for STEM: A Critical Review. *Career Development Quarterly*, *66*(1), 2–34. https://doi.org/10.1002/cdq.12119

Satorra, A., & Heijmans, R. D. H. (2000). Scaled and adjusted restricted tests in multi-sample analysis of moment structures. In Heijmans, R.D.H., Pollock, D.S.G. & Satorra, A. (eds.), *Innovations in multivariate statistical analysis*. A Festschrift for Heinz Neudecker (pp.233-247). https://doi.org/10.1007/978-1-4615-4603-0_17

Savalei, V. (2014). Understanding robust corrections in structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *21*(1), 149-160.

Schlomer, G. L., Bauman, S., & Card, N. A. (2010). Best practices for missing data management in counseling psychology. Journal of Counseling Psychology, 57, 1- 10.

Sheu, H.-B., Lent, R. W., Miller, M. J., Penn, L. T., Cusick, M. E., & Truong, N. N. (2018).

Sources of self-efficacy and outcome expectations in science, technology, engineering, and mathematics domains: A meta-analysis. *Journal of Vocational Behavior*, *109*, 118–136. https://doi-org.proxy.mul.missouri.edu/10.1016/j.jvb.2018.10.003

Soldner, M., Rowan-Kenyon, H., Kurotsuchi, I. K., Garvey, J., & Robbins, C. (2012). Supporting Students' Intentions to Persist in STEM Disciplines: The Role of Living-Learning Programs Among Other Social-Cognitive Factors. T*he Journal of Higher Education*, *83*(3), 311.

Syed, M., Zurbriggen, E. L., Chemers, M. M., Goza, B. K., Bearman, S., Crosby, F. J., … Morgan, E. M. (2018). The role of self-efficacy and identity in mediating the effects of stem support experiences. *Analyses of Social Issues and Public Policy (ASAP)*. https://doi-org.proxy.mul.missouri.edu/10.1111/asap.12170

Szelényi, K., Denson, N., & Inkelas, K. K. (2013). Women in STEM Majors and Professional Outcome Expectations: The Role of Living-Learning Programs and Other College Environments. *Research in Higher Education, 54,* 8, 851-873.

Tabachnick, B. G., & Fidell, L. S. (2007). Experimental designs using ANOVA. Thomson/Brooks/Cole.

Tate, K. A., Caperton, W., Kaiser, D., Pruitt, N. T., White, H., & Hall, E. (2015). An Exploration of First-Generation College Students' Career Development Beliefs and Experiences. *Journal of Career Development*, 42(4), 294–310.

Terenzini, P. T., And Others, & National Center on Postsecondary Teaching, L. and A. U. P. P. (1995). First-Generation College Students: Characteristics, Experiences, and Cognitive Development. AIR 1995 Annual Forum Paper. Retrieved from http://proxy.mul.missouri.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED387004&site=eds-live&scope=site

Torpey, E. (2018). Engineers: Employment, pay, and outlook," Career Outlook, U.S. Bureau of Labor Statistics. Retrieved from: https://www.bls.gov/careeroutlook/2018/article/pdf/engineers.pdf

Verdín, D., & Godwin, A. (2018). Exploring latina first-generation college students' multiple identities, self-efficacy, and institutional integration to inform achievement in engineering. *Journal of Women and Minorities in Science and Engineering*, *24*(3), 261–290.

Verdin, D., & Godwin, A. (2015). First in the family: A comparison of first-generation and non-first-generation engineering college students. *2015 IEEE Frontiers in Education Conference (FIE)*, 1.

Wasburn, M. H., & Miller, S. G. (2004). Retaining Undergraduate Women in Science, Engineering, and Technology: A Survey of a Student Organization. *Journal of College Student Retention: Research, Theory and Practice*, *6*(2), 155–168.

Ward, L., Dr., Siegel, M. J., & Davenport, Z. (2012). First-generation college students: understanding and improving the experience from recruitment to commencement. San Francisco: Jossey-Bass. Retrieved from: http://search.ebscohost.com/login.aspx?direct=true&db=cat04885a&AN=merlin.b8858727&site=eds-live&scope=site

Weston, R., & Gore, P. A. (2006). A brief guide to structural equation modeling. The Counseling Psychologist, 34, 719–751. doi:10.1177/0011000006286345

Wright, S. L., Jenkins-Guarnieri, M. A., & Murdock, J. L. (2013). Career development among first-year college students: college self-efficacy, student persistence, and academic success. *Journal of Career Development, 40*, 4, 292-310.

Yoder, B.L. (2016). *Engineering by the Numbers.* Washington DC: American Society Engineering Education. Retrieved from: https://www.asee.org/documents/papers-and-publications/publications/college-profiles/16Profile-Front-Section.pdf

Appendix A

Informed Consent Form

Broadening Participation in Engineering among Women and Latina/os: A Longitudinal, Multi-Site Study

Principal Investigators:

Lisa Y. Flores, Ph.D.
Department of Educational,
School, and Counseling Psychology
University of Missouri
Email: floresly@missouri.edu
Phone: 573-884-9724

Rachel L. Navarro, PhD.
Department of Counseling
Psychology & Community Services
University of North Dakota
Email: Rachel.navarro@und.edu
Phone: 701-777-2635

Description of Study: You have been contacted by a member of our research team to participate in a research study about the experiences of engineering students. The purpose of this research is to gain a deeper understanding of what it is like to be an engineering student. This study seeks to conduct an individual interview with you. We will also contact you to participate in a similar interview each year through 2019. The interview will consist of you answering a series of questions designed to explore your experiences as a student. Subsequent interviews will follow a similar format. Each interview session (the initial and subsequent interviews) is projected to last 1-1.5 hours and will be audio recorded. In addition, we will ask you to complete a demographic questionnaire prior to the start of the interview, which will take approximately 5-10 minutes.

Benefits and Risks: The benefits of your participation in these interviews will allow for a deeper reflection and hence a deeper understanding of your experiences as an engineering student specifically, and as a student in general. In addition, sharing your voice, opinion, and experiences will also allow for counselors, engineering educators and other students in engineering or considering engineering careers to have a better understanding of some of the challenges and benefits of entering the field of engineering. Hence, this will provide a greater avenue of support for engineering students, particularly ethnic minorities and women.

The risk of participating in this study is that people outside of the research team could link aspects of your privacy, such as your thoughts, opinions, and feelings, to your identity. To minimize those risks, the interviewer will ask you to create a pseudonym and only members of the research team will know your true identity, which will protect against the risk of a privacy violation. Expressing your thoughts and feelings regarding your experiences as an engineering student may elicit some emotion and cause you emotional discomfort.

If you feel discomfort, please call the National Suicide Prevention Line at 1-800-273-TALK or 1-800-273-8255.

Alternatively, you can log on to http://www.crisischat.org. This URL will link you with the Lifeline Crisis Chat, which can provide online emotional support, crisis intervention, and suicide prevention services. Chat specialists will listen and support you through whatever difficult times you may be facing.

Additionally, you also can call the United Way Helpline at 1-800-233-HELP or 1-800-233-4357, which can help you locate appropriate support services in your area.

Voluntary Nature of Participation: Your participation in this study is completely voluntary; therefore, you are free to end your participation at any time. If you decide not to participate, there will be no penalty.

Costs and Payments: The costs to your participation in this study are your time and the possibility of experiencing strong emotions as you reflect on your experiences as an engineering student. (Please see list of support resources above). If you decide to participate in the interview, you will receive a $25 gift certificate.

Confidentiality: Any information obtained about you from this research, including answers to interview questions, will be kept strictly confidential. The data derived from this study could be used in reports, presentations, and publications, but you will never be individually identified. Any information linked to you will be associated with a pseudonym. The only link between your true identity and your pseudonym will be known by the members of the research team. The informed consent document, which you will be asked to sign, will be kept in a locked desk drawer to which only the research team members have access. The document linking your research ID number with your pseudonym will be stored on a secured electronic folder, and deleted at the end of the study.

Signature: Checking the "I agree" box below means that you have freely agreed to participate in this research study. You should only consent if you have read this form or if it has been read to you and you fully understand its contents. If you have any questions about this research, please contact the Principal Investigators at the phone number or emails listed above. If you have any questions about your rights as a research participant or for more information regarding participation in this research, please feel free to contact the University of Missouri-Columbia Campus Institutional Review Board office at 573-882-9585 or the University of North Dakota Institutional Review Board office at (701) 777-4279.

☐ No, I do not agree to participate in this research study.

☐ Yes, I agree to participate in this research study.

Participant Signature ______________________________ Date __________

Researcher Signature ______________________________ Date __________

Appendix B

Demographic Information

Directions: *The following are some questions about you and your family. Please **fill in, check, OR circle** the best description of you and your family members.*

1. Your Age: _____

2. Your Sex:

a. Female
b. Male

4. Circle the generation that best applies to you.

a. 1st generation (you were born in Mexico or other country)
b. 2nd generation (you were born in USA; either parent born in Mexico or other country)
c. 3rd generation (you were born in the USA; both parents born in USA and all grandparents born in Mexico or other country)
d. 4th generation (your and your parents born in USA and at least one grandparent born in Mexico or other country with remainder born in the USA).
e. 5th generation (you and your parents born in the USA and all grandparents born in the USA)

5. Class Standing:

a. Freshman
b. Sophomore
c. Junior
d. Senior
e. Other (please specify) _________________

6. Please identify your intended major:

a. Chemical Engineering
b. Civil Engineering
c. Electrical and Computer Engineering
d. Engineering Physics
e. Engineering Technology
f. Industrial Engineering
g. Information and Communication Technology
h. Mechanical Engineering
i. Aerospace Engineering
j. Surveying Engineering

7. Who is the female head of your household? (e.g., the adult woman who provides/provided for you in terms of food, housing, clothing, and other resources)

a. your mother
b. your step-mother
c. your sister
d. your grandmother
e. your aunt
f. other (please specify ________________)

8. What is the current marital status of the female head of your household?

a. single, never married
b. married
c. divorced
d. remarried
e. widowed
f. separated

9. Who is the male head of your household? (e.g., the adult man who provides/provided for you in terms of food, housing, clothing, and other resources)

a. your father
b. your step-father
c. your brother
d. your grandfather
e. your uncle
f. other (please specify)

10. What is the current marital status of the male head of your household?

a. single, never married
b. married
c. divorced
d. remarried
e. widowed
f. separated

11. Do the adult(s) who are the head(s) of your household own his/her/their own home?

a. Yes
b. No

12. How would you identify your social class?

a. working class
b. middle class
c. upper class

Directions for questions 13 and 14: *Please place an **X** in the appropriate spot for your Mother's and your Father's level of school completed and for your Mother's and Father's occupation. If you grew up in a single parent household, you only need to complete this for the parent you grew up with.*

13.

Level of School Complete	**Mother (Female head of household)**	**Father (Male head of household)**
Less than 7th grade		
Junior high (9th grade)		
Partial high school (10th or 11th)		
High school graduate		

Partial college (at least one year)		
College graduate		
Graduate degree		

14.

<u>Occupation</u>	**Mother (Female head of household)**	**Father (Male head of household)**
Farm laborer, day laborer.		
Unskilled worker, service worker.		
Machine operator, semiskilled worker.		
Skilled manual worker, craftsman, police and fire services, enlisted military and non-commissioned officers.		
Clerical/sales, small farm owner.		
Technicians, semi-professional, supervisor, office manager.		
Small business owner, farm owner, teacher, low level manager, salaried worker		
Mid-level manager or professional (for example: architect, engineer, accountant, attorney), mid-size business owner, military officer		
Senior manager or professional (for example: physician, college professor, minister) owner or CEO of large business.		

Appendix D

Engineering Self-Efficacy
Lent et al. (2005)

Instructions: The following is a list of major steps along the way to completing an engineering degree. Please indicate how much confidence you have in your ability to complete each of these steps in relation to the major you are most likely to pursue. Use the scale below to indicate your degree of confidence.

How much confidence do you have in your ability to:	**No Confidence**									**Complete Confidence**
1. Complete all of the "basic science" (i.e., math, physics, chemistry) requirements for your engineering major with grades of B or higher	0	1	2	3	4	5	6	7	8	9
2. Excel in your engineering major over the next semester	0	1	2	3	4	5	6	7	8	9
3. Excel in your engineering major over the next two semesters	0	1	2	3	4	5	6	7	8	9
4. Complete the upper level required courses in your engineering major with an overall grade point average of B or better	0	1	2	3	4	5	6	7	8	9

Appendix E

Negative Outcome Expectations - Engineering
Lee et al. (2016)

Instructions: Using the scale 0 to 9 below, please indicate the extent to which you agree or disagree with each of the following statements.

Graduating with a degree in engineering will likely result in	**Strongly Disagree**									**Strongly Agree**
1. Not having a personal life	0	1	2	3	4	5	6	7	8	9
2. Facing complaints from my partner and family due to long working hours	0	1	2	3	4	5	6	7	8	9
3. Doing boring work	0	1	2	3	4	5	6	7	8	9
4. Limited access to mentors who understand me	0	1	2	3	4	5	6	7	8	9
5. Increase my sense of self-worth	0	1	2	3	4	5	6	7	8	9
6. Needing extensive, additional training beyond a bachelor's degree	0	1	2	3	4	5	6	7	8	9
7. Feeling like an outcast among family and friends	0	1	2	3	4	5	6	7	8	9
8. Difficulty finding a partner who respects my career choice	0	1	2	3	4	5	6	7	8	9
9. Worrying about being perceived negatively because of plans to have family or already having a family	0	1	2	3	4	5	6	7	8	9
10. Being less attractive to friends	0	1	2	3	4	5	6	7	8	9
11. Challenges balancing between work responsibilities and family obligations	0	1	2	3	4	5	6	7	8	9
12. Not having time to maintain current friendship(s) or begin new ones	0	1	2	3	4	5	6	7	8	9
13. Feeling frustrated with challenging tasks	0	1	2	3	4	5	6	7	8	9
14. Feelings of tokenism, or feeling that I am being stereotyped	0	1	2	3	4	5	6	7	8	9
15. Having difficulty finding time to date	0	1	2	3	4	5	6	7	8	9
16. Not receiving promotions because of my gender	0	1	2	3	4	5	6	7	8	9
17. Having a job that is uninspiring	0	1	2	3	4	5	6	7	8	9
18. Feeling like an outcast among potential romantic partners	0	1	2	3	4	5	6	7	8	9
19. Limited availability of role models who are like me.	0	1	2	3	4	5	6	7	8	9
20. Having a tedious job	0	1	2	3	4	5	6	7	8	9
21. Receiving a lower salary than my peers for equal work and qualifications	0	1	2	3	4	5	6	7	8	9

Appendix F

Engineering Persistence Intentions (EPI/Goals)
Lent et al. (2013)

Instructions: Using the scale below, indicate your level of agreement with each of the following statements.

How much do you agree or disagree with the following statements	Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
1. I intend to major in an engineering field	1	2	3	4	5
2. I plan to remain enrolled in an engineering major over the next semester	1	2	3	4	5
3. I think that earning a bachelor's degree in engineering is a realistic goal for me	1	2	3	4	5
4. I am fully committed to getting my college degree in engineering	1	2	3	4	5

Appendix G

Persistence in Engineering
(Actions)

Instructions: What is your current status in engineering?

1. Graduated with bachelor's degree & employed
2. No longer enrolled in college (i.e., left college without earning a degree) & employed
3. No longer enrolled in college (i.e., left college without earning a degree) & unemployed
4. Current graduate student & unemployed
5. Current graduate student & employed
6. Graduated with bachelor's degree & unemployed
7. Current undergraduate majoring in Engineering
8. Current undergraduate not majoring in Engineering

Appendix H

In-College STEM Program Participation

Instructions: During your undergraduate career, did you participate in any programs that focused on STEM? Examples include *NMSU-MARC (Minority Access to Research Careers), HS-STEM summer Internship Program, and ACCESS-Achieving Competence in Computing, Engineering, and Space Science.*

Yes
No

VITA

David Diaz was born on February 14, 1987 in Los Angeles, CA. He obtained his bachelor’s degree in Psychology, with a minor in Education and Applied Psychology, from the University of California, Santa Barbara. Additionally, he obtained his master’s degree in Clinical Psychology with an emphasis in Marriage and Family Therapy from Pepperdine University. He is currently a doctoral candidate in Counseling Psychology at the University of Missouri-Columbia. His graduate training and professional interests include working with college students from under-represented backgrounds.