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Perception Matters: Student Educational Experiences in COVID-19 are related to Engineering Self-Efficacy and Persistence Intentions*

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This study examined COVID-19's impact on the career goals of undergraduate engineering students through the lens of Social Cognitive Career Theory. The participants were enrolled as engineering majors at a Hispanic Serving Institution (n = 540) and a Historically Black University/College (n = 69) and completed measures of engineering self-efficacy, engineering outcome expectations, major career goals, and the impact of COVID-19 on educational experiences and network support. The study found that the hypothesized model fit the data well across both campuses studied. Of particular interest, student perceptions of COVID-19's impact on their educational experience was strongly related to their engineering self-efficacy, and this, COVID-19's impact on education experience was found to have an indirect effect on student persistence intentions through self-efficacy for both campuses. Specifically, students who reported a more positive COVID-19 educational experience had higher engineering self-efficacy scores, which in turn resulted in higher intentions to persist in their engineering major. Conversely, as a student perceived their educational experience during COVID-19 to be more negative, their engineering self-efficacy was more likely to decrease, which resulted in their being less likely to intend to persist in their engineering degree. Implications and future directions are discussed.

Keywords: Social Cognitive Career Theory; COVID-19; Self-efficacy; Outcome Expectations; Persistence; Hispanic Serving Institute; Historically Black University/College

1. Introduction

1.1 Statement of the Problem

Job growth over the next decade in Science, Technology, Engineering, and Math (STEM) is projected to increase two times faster than in other occupations in the United States [1]. Engineering jobs are expected to see an 8% increase between 2016 and 2026, primarily in the civil, mechanical, industrial, and electrical engineering sectors [2]. While the number of engineering bachelor's degrees has increased since 2000 [3], the growth has been unable to keep up with the demands of the U.S. economy [4]. Further, COVID-19 disrupted education for millions of students. Using social cognitive career theory as a lens to view student matriculation into engineering careers, the purpose of this study is to examine the impact of COVID-19 student persistence intentions at two universities (a Hispanic Serving Institution and a Historically Black University/College).

1.2 Persistence in Engineering

Although problems exist in attracting pre-college students to STEM careers [5–7], a greater concern is the retention rate of undergraduate students once they've enrolled in a STEM major. Chen [8] found that 48% of bachelor's degree students enrolled in STEM majors from 2003 to 2009 had left the field by the spring of 2009, with almost half of them transitioning to non-STEM fields. Attrition rates are highest during the first two years of a STEM program, with 50% of students leaving after their first year and 30% after their second year [9]. Looking specifically at under-represented populations, women and historically marginalized minorities often have a higher attrition rate in engineering than their peers [8, 10]. Weston [9]

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reported that women (18.3%) had higher rates of switching to non-STEM fields than males (11%). When looking at racial/ethnic groups (males and females), underrepresented minorities switched majors at a higher rate than other students; specifically, African Americans (22%) and Hispanics (19%) had the highest likelihood of leaving the field [9]. Increasing diversity is one method to ensure a wide range of perspectives in STEM fields; however, little is known about the effect of COVID-19 on undergraduate programs and how that might have affected underrepresented populations.

1.3 COVID-19 Impact

The effect of COVID-19 on education is still unknown, but the National Center for Education Statistics [11] estimates that 16.2 million undergraduate students experienced a disruption in learning during the pandemic. In September 2020, university presidents indicated fiscal budgets and student enrollment were leading concerns emerging from the COVID-19 disruptions [12]. Compared to Fall 2019, enrollment rates dropped by 7.8% during the Fall 2020 and 2021 semesters; notably, science and engineering programs saw only a 5.4% decrease [13]. A survey of 4000 bachelor's degree students mirrored administrative concerns regarding student enrollment; specifically, 67% of respondents admitted they had considered withdrawing from classes, and 50% believed COVID-19 would negatively influence their ability to complete their undergraduate programs [14]. In a survey of 1500 undergraduate students, respondents indicated they were concerned that the pandemic would have a long-term effect on the job market [15]. The effect of COVID-19 goes beyond post-secondary enrollment and employment opportunities. Students have indicated food security [16], caregiving responsibilities [17], financial hardship [18], digital disparities [19], and mental health [20] as potential roadblocks to completing a bachelor's degree program. The effect of COVID-19 on engineering students is unknown, but it is of particular concern due to the already high attrition rate that exists under normal circumstances.

Remote or online learning is not a new concept in education [21]. During the 2018–2019 academic year, most colleges (79%) offered distance education courses or programs [11]. While traditional in-person engineering courses have focused on content, design, and critical thinking skills, Bourne, et al. [22] state that for an online alternative to be successful, they must be high quality, easily accessible, and cover a variety of topics. Education disruption caused by the COVID-19 pandemic forced universities to shift their programs and course offerings entirely to remote learning to ensure the safety of students, faculty, and staff. While some universities expressed intentions to return to business as usual for the Fall 2020 semester [23], a survey of 3000 universities in October 2020 showed that 34% chose to continue to provide online courses and 21% opted for hybrid models [24]. In a survey of engineering students and faculty members from a California university, logistical/technical problems, privacy and security concerns, and the lack of hands-on training were all challenges believed to influence remote learning negatively [25]. Additionally, students indicated a lack of engagement, decreased focus, and increased fatigue from attending multiple Zoom sessions [25]. Due to the unexpected transition to online learning necessitated by COVID-19, student intentions and development into engineering careers may have been altered. We examine next social cognitive career theory (SCCT) to illustrate how students matriculate into careers – namely, engineering.

2. Conceptual Framework

SCCT is rooted in Bandura's [26] social cognitive theory, linking learning and cognitive development to career development processes over time [27]. SCCT is composed of three interconnected models that are hypothesized to explain (a) career interest development, (b) career choice, and (c) performance and persistence. The primary body of the model consists of social cognitive variables such as self-efficacy, outcome expectations, and personal goals (goals). Bandura [26] describes self-efficacy as a person's belief that they can perform a specific behavior, while outcome expectations refer to the belief that a specific action will lead to a specific result or consequence. Goals are the decisions to participate in a certain activity or work towards a particular outcome [27]. SCCT focuses on understanding the conditions that promote or hinder a person's actions or choices in pursuing their career goals [28]. Previous studies are used to provide an overview of the main components of the SCCT model, followed by a literature summary of SCCT's use in studying gender and diverse populations.

The choice and interest models of the SCCT are primarily applied to high school students who have yet to choose a major in college. The performance model is applied to college students who have declared a STEM major and is used by researchers to describe a person's performance or persistence within a major. Because our participants are college students who have already selected their major, the performance model was utilized. The performance model hypothesized that self-efficacy would have

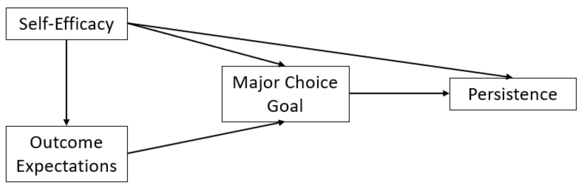

Fig. 1. The Performance/Persistence Model.

both direct and indirect effects on performance/persistence through goals (Fig. 1; [27]). Additionally, outcome expectations would indirectly influence performance through goals and actions [27]. SCCT has been used to explore career development among engineering students over the last 25 years; however, the performance model has been the least studied in the research [28, 29]. Research utilizing SCCT models has found statistically significant and positive effects of self-efficacy on outcome expectations [30–32], which in turn affects goals [33, 34], which in turn affects persistence [29, 35, 36].

In the performance model, self-efficacy is well assessed in the literature. The concept explains the motivation behind a person's behavioral choices, including activity choice or how a feeling of incompetence can lead to situational avoidance [37]. People with a higher sense of self-efficacy are considered more likely to expend greater effort on a task and persist in the face of obstacles [38]. Research has shown that self-efficacy is highly correlated with academic performance [27, 39, 40] and is present in models of retention and persistence [27, 35, 41]. In a systematic review and meta-analysis, Richardson, et al. [40] found strong correlations between undergraduate GPA, student performance self-efficacy, grade goals, effort regulation, and academic self-efficacy. Students with high self-efficacy were more likely to self-regulate using goal setting, self-monitoring, and learning strategies [42] which in turn are related to better time management, task persistence, and problem-solving [43]. Researchers have verified self-efficacy's convergent validity making it an effective predictor of students' activity choices, effort, and persistence [42].

Despite outcome expectation's presence in the original performance model, Brown, et al. [29] found that most research had focused on the paths from self-efficacy to academic performance and persistence, while outcome expectations had rarely been a research focus. This is potentially because of outcome expectations' small predictive power, in the original SCCT study, Lent, et al. [27] found that outcome expectations (0.10) only had a small correlation to future performance. Yet outcome expectations is an important addition to the performance model since it is the mechanism in which self-efficacy operates on goals. In a longitudinal study of the integrative SCCT model, Lent, et al. [35] full sample analysis found that persistence in engineering measured at the end of a student's sixth semester was predicted by persistence goals, academic satisfaction, and self-efficacy measured at the end of a student's second semester. Variables measured at the end of a student's first semester that were indirectly linked to persistence included self-efficacy and outcome expectations [35]. Despite outcome expectations' limited use in SCCT it is an important component of the performance model, and additional research is needed to study its impact on student persistence.

2.1 SCCT and Race/Ethnicity

Research findings have noted differences in self-efficacy among racial/ethnic groups. A study predicting engineering interests and major choice goals among students at historically Black and predominantly White universities found that self-efficacy was the primary predictor for career goals among both groups of students [44]. When examining the relations between intended persistence across race/ethnicity, Navarro, et al. [36] found that the model explained variance for self-efficacy (34.9%) and persistence (18.1%) was slightly higher for Latino students than for their White peers. In a study of research self-efficacy on career intentions, Byars-Winston and Rogers [30] found similar results among African American and Hispanic undergraduates, in that research self-efficacy was a significant positive predictor of career intentions. Byars and Hackett [45] posited that students' personal backgrounds, such as race/ethnicity, could influence students' learning experiences, which would significantly impact academic achievement and career choice. This could also be true for socioeconomic status, in which MacPhee, et al. [46] found that students who were considered as a double minority – underrepresented race/ethnicity and low socioeconomic status – had lower self-efficacy and performance than their single disadvantaged peers, with effect sizes between 0.43 and 0.62. Additionally, in an examination of STEM confidence among undergraduate engineering students, Litzler, et al. [47] found that their initial results were in line with the literature in that confidence among White men was significantly higher than for the underrepresented group participants. However, once student experience, perceptions, GPA, and other demographic factors were controlled in the model, African American and Hispanic men reported higher STEM confidence levels than White men. In contrast, African American and Hispanic women reported similar confidence levels to White men [47]. The United States population is diverse; however, the engineering workforce

Table 1. Sample Demographics (HSI n = 540; HBCU n = 69)

Demographic	HSI	HBCU	Total
American Indian or Alaskan Native (1)	0	1	1
Asian (2)	139	0	139
Black or African American (3)	14	58	72
Hispanic, Latino, or Spanish (4)	74	5	79
Middle Eastern or North African (5)	8	1	8
Multiracial (6)	61	3	64
White (8)	232	0	232
Prefer not to respond (9)	11	1	12
A race, ethnicity, or origin not listed (10)	1	0	1
Year in School			
Sophomore	158	18	176
Junior	194	25	219
Senior, inclusive of 5th year seniors	188	26	214
Gender			
Male	348	40	388
Female	175	28	203
First Generation Student			
Yes	96	20	116
No	440	49	489

Note: Not all participants answered every question.

does not reflect this diversity. The literature illustrates that student ethnicity is related to self-efficacy and is helpful in predicting persistence among undergraduate students.

2.2 Current Study

Our study investigates the impact of COVID-19 on persistence intentions at two distinct campuses, a Hispanic Serving Institution (HSI) and a Historically Black University/College (HBCU). Specifically, we examined two areas that may have impacted their matriculation into an engineering career: (a) their undergraduate educational experiences and (b) their ability to build an engineering support network. We used these data to address the following question:

How did students' perceptions of the impact of COVID-19 influence their career development as viewed through social cognitive career theory?

3. Methods

Through an institutional grant, faculty members within the College of Education and the College of Engineering at two universities in the Southwest administered a survey to measure how COVID-19 impacted the performance and persistence of undergraduate engineering students. The survey was administered in April 2022 and was composed of 87 Likert-style and open-ended questions. For this study, the analysis focused on the pedagogical impact of COVID-19 on student learning (n = 7), self-efficacy (n = 3), engineering outcome expectations (n = 3), and goals (n = 5). The survey also collected demographic information for respondents, including race/ethnicity, gender, major, student classification, and first-generation status (Table 1). A total of 735 participants responded to the survey; however, for this analysis, we extracted responses from students who would have attended the university during the early part of the pandemic, Fall 2020. Participants were removed from the data set if they did not consent, were classified as either first-year or graduate students or were missing data on all our measured variables (n = 126). The final sample included 609 participants at both campuses. Additionally, a small number of participants in the survey self-identified as fifth-year seniors (n = 17); these students were recoded as seniors. The final sample included undergraduate engineering students attending either an HSI (n = 540) or an HBCU (n = 69). The sample comprised sophomores (n = 176), juniors (n = 219), and seniors, inclusive of students in their fifth year (n = 214).

4. Instrument

Engineering self-efficacy. The engineering self-efficacy scale [44] is a 3-item measure (α = 0.85) used to assess participants' confidence in their ability to complete important steps in their pursuit of an engineering degree. Participants responded using a five-point Likert scale ranging from 1 (no confidence) to 5 (complete confidence).

Engineering outcome expectations. The outcome expectations in engineering scale [44] lists three positive outcomes that could result from a student's obtaining an engineering degree (α = 0.88). Participants responded using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Major choice goals. The major choice goals scale ([goals], [44]) uses five measures to indicate a student's academic intentions. During analysis, two items on this scale were omitted. The first item, "I plan to remain enrolled in an engineering major over the next semester" was originally used in a survey of underclassmen. The current study included a larger proportion of upperclassmen who may have chosen a negative response due to graduation plans. The second item omitted was negatively worded, "I am considering switching to another major" and not well correlated with the other items indicating students responded to the item differently than they did the positively worded items. The revised scale demonstrated acceptable reliability (α = 0.73). Participants responded using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

COVID-19 impact. The COVID-19 impact scale listed seven possible effects of pursuing an engineering degree during the pandemic. The scale consisted of two factors, the first lists four items focused on students' undergraduate educational experiences (e.g., "ability to take more advanced engineering courses"), and the second lists three items focused on students' ability to build an engineering support network (e.g., "make connections for the job market"). Participants responded using a 100-point scale ranging from –50 (negatively impacted) to 50 (positively impacted). The data were subjected to exploratory factor analysis with principal axis factoring and direct oblimin rotation. A parallel analysis [48] and Velicer's Minimum Average Partial (MAP) test [48, 49] – both the original and revised MAP – indicated two factors. Thus, two factors were extracted. In the rotated solution, four items loaded onto the first factor, COVID-19 education: the impact of COVID-19 on educational experience, and three items loaded onto the second factor, COVID-19 network: the impact of COVID-19 on building a support network. All factor loadings on the primary factor ranged from 0.58 to 0.94. Secondary factor loadings were less than 0.20. A Cronbach's alpha for COVID-19 education and COVID-19 network were acceptable (α = 0.80, α = 0.82, respectively).

4.1 Plan of Analysis

We used multigroup confirmatory factor analysis to test measurement invariance across participants from different campuses [50]. Each factor in the model was tested to determine if the participants from different campuses interpreted the construct similarly. Scalar measurement invariance was obtained for self-efficacy, outcome expectations, COVID-19 impact on educational experiences, and goals. Invariance was not obtained for COVID-19 network support; however, it was retained in the model due to its relevance to the research question – because the factor loadings for the items were not the same across the students at the two universities, the effects of COVID-19 network support should not be compared across campuses but interpreted separately.

Using data from both campuses, we examined whether COVID-19 directly affected or moderated the relationships among the constructs in the model. Although we tested for potential moderations of the three paths specified in the SCCT model by the two COVID-19 constructs, only the direct paths are illustrated for simplicity in Fig. 2. Specifically, we employed a multi-group structural equation model. We started with a model in which all

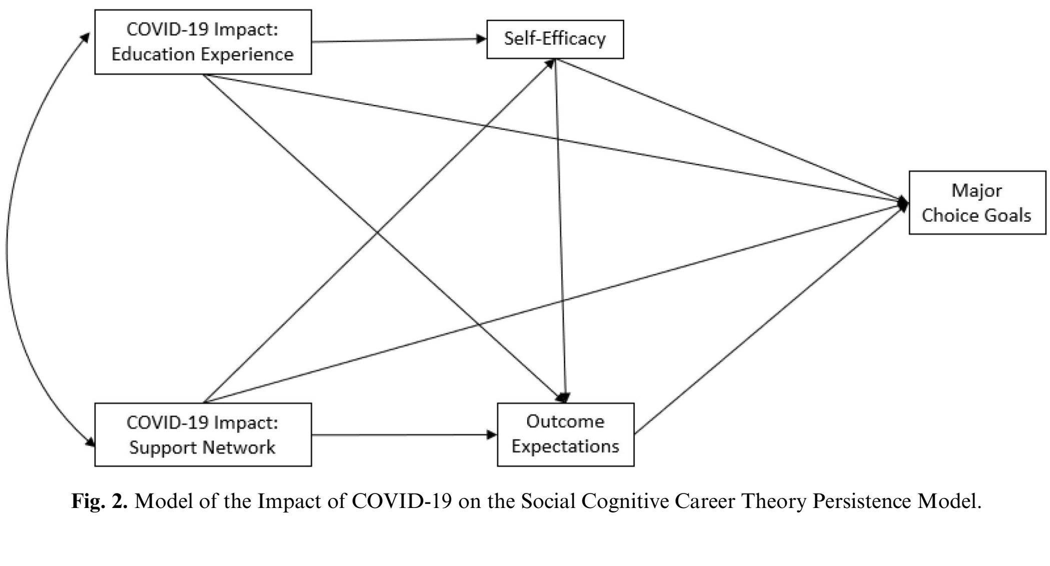

Fig. 2. Model of the Impact of COVID-19 on the Social Cognitive Career Theory Persistence Model.

paths were freely estimated across the two campuses. Next, we constrained all paths to be the same across the two campuses [51]. Because chi-square tests can be overly sensitive, we assessed acceptable model fit by the following indicators (a) Comparative Fit Index (CFI) exceeding 0.90 [52], root mean square error of approximation (RMSEA) below 0.08 or a 90% confidence interval that contained 0.05 [53], and standardized root mean squared residual (SRMR) of 0.08 or less [54]. All indirect effects were assessed using bootstrap confidence intervals over 2000 replications.

5. Results and Analysis

5.1 Descriptive Statistics

Pearson Correlation analysis was used to examine the relationships between the variables in the hypothesized model for both campuses (Table 2). Results indicated that the relationships for both campuses were consistent with SCCT. Self-efficacy was moderately correlated to outcome expectations for the HSI campus and strongly correlated for the HBCU. Additionally, outcome expectations were strongly correlated to goals for both campuses. COVID-19 education showed a small relationship to self-efficacy for both campuses, while COVID-19 network had no statistically significant relationships across the main SCCT variables for both campuses. Further, the relationship between COVID-19 education and COVID-19 network appears to be stronger at the HBCU than at the HSI.

5.2 Full Sample Analysis

We utilized a structural equation model (SEM) with observed variables to address our research question. All analyses were conducted using Mplus Version 8.8 [55]. Descriptive statistics and correlations are reported in Table 2 and Table 3. An initial model was built that included all specified paths; specifically, we examined whether COVID-19 had a direct effect on or moderated the relationships among the constructs in the model (Fig. 2). These results indicated that the moderated model was a poor fit to the data (χ^2 [df = 45] 78.87, $p < 0.001$), CFI = 0.86, SRMR = 0.07, and RMSEA = 0.008). The moderated paths were subsequently removed from the analysis. After trimming the model of the moderation effects, there was a statistically significant direct effect from COVID-19 education to self-efficacy. The final model, which was just-identified, provided an acceptable fit to the data (χ^2 [df = 0] 0.00, $p < 0.001$, CFI = 1.00, RMSEA < 0.001, and SRMR < 0.001). Even though this was a just-identified model, the effects of COVID-19 network should be viewed with caution since we did not achieve metric invariance for this factor. The statistically significant paths were outcome expectations on goals (β = 0.61, b = 0.55, p = <0.001), COVID-19 education on self-efficacy (β = 0.30, b = 0.02, p = <0.001), and self-efficacy on outcome expectations (β = 0.36, b = 0.44, p = <0.001). The proportion of variance explained by the model was 36% for goals, 8% for self-efficacy, and 13% for outcome expectations.

5.3 Multi-Group Structural Equation Model

We next tested potential differences in the effect of COVID-19 on the variables in the SCCT model at the different campuses. First, we ran an unconstrained model that allowed the paths to vary between the campuses. Next, we ran a model in

Table 2. Correlation Matrix of the Model Variables for Two Groups

	1	2	3	4	5
Engineering Self-efficacy	–	0.46*	0.40*	0.25	0.14
Engineering Outcome Expectations	0.33*	–	0.67*	–0.09	–0.09
Major Choice Goals	0.15*	0.57*	–	0.0008	–0.05
COVID-19 Impact: Education Experience	0.27*	0.09	0.05	–	0.74*
COVID-19 Impact: Support Network	0.05	0.02	0.009	0.36*	–

Note: Correlations for an HSI (n = 409) are to the left and below the diagonal lines. Correlations for an HBCU (n = 53) are to the right and above the diagonal line. Correlations denoted with a * are statistically significant at p < 0.001.

Table 3. Means, Standard Deviations, and Reliability Coefficients for the Variables of Interest

	HSI				HBCU				Item Scale
	N	Mean	SD	α	N	Mean	SD	α	
Engineering Self-Efficacy	415	0.06	0.85	0.85	53	0.12	0.85	0.93	1 to 5
Engineering Outcome Expectations	418	–0.01	1.04	0.88	53	–0.68	1.13	0.89	1 to 7
Major Choice Goals	412	6.17	0.97	0.73	53	6.39	0.80	0.79	1 to 7
COVID-19 Impact: Educational Experience	418	0.29	15.27	0.80	53	–0.28	20.16	0.85	–50 to 50
COVID-19 Impact: Support Network	418	–0.08	18.71	0.82	53	–0.79	26.39	0.89	–50 to 50

Table 4. Summary of Goodness of Fit Indices for Multi-group Model

Model	χ^2	*df*	*p*-value	CFI	SRMR	RMSEA	$\Delta\chi^2$	Δ*df*
1. Full Sample	0.000	0	<0.001	1.00	<0.001	<0.001		
2. Unconstrained by Campus	0.000	0	<0.001	1.00	<0.001	<0.001		
3. Fully Constrained by Campus	31.10	10	0.0006	0.94	0.06	0.08	31.10	10

which all paths were constrained to be equal between the two campuses. The fit indices shown in Table 4 indicate that the constrained model provided an acceptable fit to the data.

We were interested in predicting goals from self-efficacy, outcome expectations, and the impact of COVID-19 on engineering students. The theoretically supported paths and the statistically significant paths of interest are illustrated in Fig. 2. As expected, self-efficacy was a statistically significant positive predictor of outcome expectations for both groups; however, the theoretically expected paths from self-efficacy to goals were not statistically significant for either group (Table 5). The path coefficient from outcome expectations was also a statistically significant positive predictor of goals for both groups. For students who attended the HSI, COVID-19 education was positively related to self-efficacy (β_{HSI} = 0.31, b = 0.02, SE = 0.05, p = <0.001). Specifically, for students at the HSI who had a COVID-19 educational experience that was 1 standard deviation above average, their engineering self-efficacy was expected to be 0.31 standard deviations units higher. Similarly, for students at the HSI with a COVID-19 education experience of 1 standard deviation below average, their engineering self-efficacy was expected to be 0.31 standard deviations lower.

For students who attended the HBCU, COVID-19 education was also positively related to self-efficacy (β_{HBCU} = 0.32, b = 0.02, SE = 0.06, p = <0.001). Specifically, for students at the HBCU who had a COVID-19 educational experience that was 1 standard deviation above average, their engineering self-efficacy was expected to be 0.32 standard deviations units higher. Similarly, for students at the HBCU with a COVID-19 educational experience of 1 standard deviation below average, their engineering self-efficacy was expected to be 0.32 standard deviations lower.

Next, we examined whether COVID-19 education experiences had a mediated effect on goals through self-efficacy and outcome expectations: COVID-19 education → self-efficacy → outcome expectations → goals. Each path was positive and statistically significant. Testing the indirect effect of COVID-19 education on goals through self-efficacy and outcome expectations for the HSI (β_{HSI} = 0.06, p < 0.001, 95% CI [0.04, 0.09]) and the HBCU (β_{HBCU} = 0.09, p = <0.001, 95% CI [0.06, 0.13]). The statistically significant indirect effect indicated COVID-19 had a small effect on major goals through its impact on engineering self-efficacy, which in turn impacted engineering outcome expectations, which impacted major goals. Specifically, students who indicated COVID-19 positively impacted their education experience were more likely to have positive engineering self-efficacy leading to greater persistence in major goals–and the opposite was expected for students who indicated a more negative educational experience due to COVID-19.

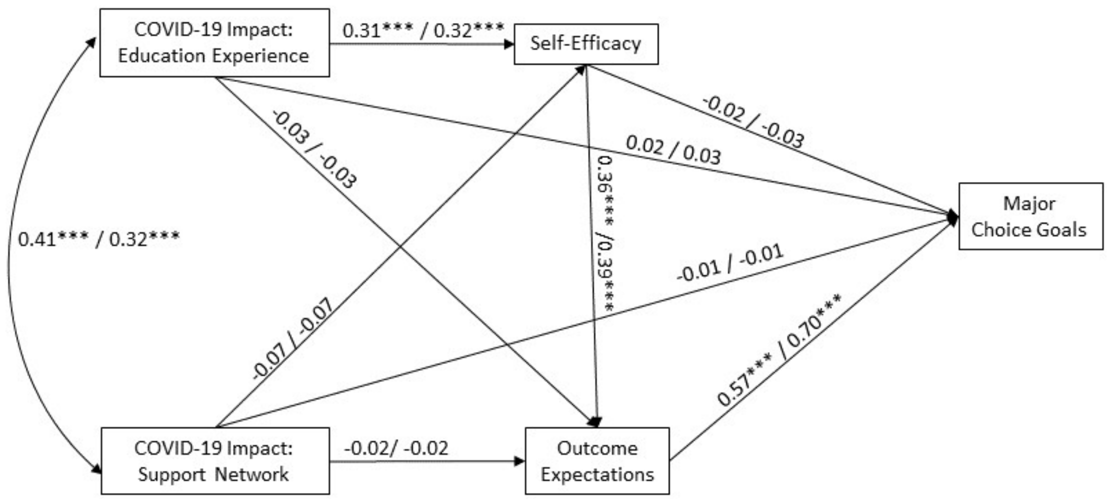

Fig. 3. Standardized Estimates of the SEM Path Analysis of the Impact of COVID-19 (educational impact) on Major Choice Goals. Note: Standardized path coefficients are presented for HSI are before the slash and the HBCU after the slash. *** p < 0.001.

Table 5. Summary of Standardized Path Coefficients by School Type

Dependent Variable	Predictors	Hispanic Serving Institution			Historically Black University or College		
		β	SE	p	β	SE	p
Engineering Self-efficacy	COVID-19 Impact: Educational Experience	0.31	0.05	<0.001	0.32	0.06	<0.001
	COVID-19 Impact: Support Network	–0.07	0.05	0.20	–0.07	0.06	0.21
Engineering Outcome Expectations	Self-efficacy	0.36	0.04	<0.001	0.39	0.07	<0.001
	COVID-19 Impact: Educational Experience	–0.03	0.05	0.59	–0.03	0.05	0.60
	COVID-19 Impact: Support Network	–0.02	0.04	0.64	–0.02	0.05	0.65
Major Choice Goals	Self-efficacy	–0.02	0.04	0.58	–0.03	0.05	0.57
	Outcome Expectations	0.57	0.04	<0.001	0.70	0.08	<0.001
	COVID-19 Impact: Educational Experience	0.02	0.04	0.59	0.03	0.06	0.59
	COVID-19 Impact: Support Network	–0.01	0.04	0.84	–0.01	0.06	0.85

6. Discussion and Implications

COVID-19 has impacted undergraduate students' educational experiences across the United States. This study aimed to investigate undergraduate students' perceptions of how COVID-19 impacted their career goals as viewed through SCCT. This study adds to the literature by comparing the effects of COVID-19 on student persistence for undergraduate engineering students at an HSI and HBCU. Three results are notable: (1) observed effects mostly replicate what the previous literature has found, (2) the hypothesized model fits the data well for the full sample and across both campuses studied, and (3) the educational impact of COVID-19 on persistence through self-efficacy was strong on both campuses, but the impact of COVID-19 relative to the ability to build a network were not related to any aspect of the SCCT model. Next, we discuss each in turn.

The performance model of SCCT hypothesized that self-efficacy would have both a direct and indirect effect on a student's persistence through their major choice goals [27]. The base model of SCCT used in our model resulted in slightly different effects from what has been found in the literature. The data used was cross-sectional with a single time point which limits our ability to draw conclusions about the effect of COVID-19 on student persistence. While the bivariate correlation between self-efficacy and goals was statistically significant, once the other variables in the model were introduced, self-efficacy no longer predicted student goals. self-efficacy did have the predicted indirect effect on goals through outcome expectations. Despite outcome expectations' presence in the SCCT model, it is rarely the focus of research studies [29]. Our research extends the literature by showcasing that outcome expectations is a mechanism by which self-efficacy can operate on goals.

COVID-19's effect on educational experience directly impacted student self-efficacy, impacting their outcome expectations and, eventually, their goals. Students at the HSI campus reported a slightly negative effect of COVID-19 on their educational experience, while students at the HBCU reported a slightly more positive effect. While the average scores at the two campuses differed, the relationship between those scores and self-efficacy was not different at the two campuses. Students who reported a more positive COVID-19 educational experience had higher self-efficacy scores and were more likely to intend to persist in engineering – and vice versa. A consideration for why some students may have had a more positive educational experience during COVID-19 may have been due to instructional adjustments and accommodations to courses. For example, some of the recorded accommodations by university researchers included online learning, recorded lectures, and homework solutions [56], virtual or in-home laboratories [57], flexibility in asynchronous courses [58], and relaxed grading policies [59]. These accommodations may have helped some students overcome the initial roadblocks to pursuing a bachelor's degree during COVID-19 lockdowns and safety measures. This study's findings replicate and expand prior findings that there were no differences across groups, gender or race/ethnicity when using the SCCT model [28, 33, 36, 60]. Our results indicated there were no differences between students at the HSI and HBCU campus, and students at both types of campuses developed similarly.

We want to note some of the limitations of this study. First, this study was conducted with a convenience sample and may not represent all students who attended these two universities. Navarro, et al. [31] found that when groups were examined considering their social identities or social environments, then variations across groups did occur. Future research should consider diverse populations and how personal, environmental, and behavioral factors may influence student persistence and success. Further, students' self-efficacy was impacted by their perceptions of COVID-19's impact on their educational experience. The positive experience indicated by most students may be due to the timing of the study. Students were surveyed towards the end of the Spring 2022 semester when many state lockdowns and safety measures were lessening. If students had been surveyed at the beginning of the pandemic, they may have perceived COVID-19 to have a more negative effect on their educational experiences. Additionally, students who took part in the survey would have had varying degrees of educational experiences based on their academic classification. Sophomore students would only have had university experiences that were shaped by COVID-19, while juniors and seniors would have begun their academic careers in a more traditional setting. Selection bias is a concern since students who participated in the study were students who had continued to persist in their studies through COVID-19. Researchers may need to look at the possible impacts of COVID-19 on a much broader scale, to determine how COVID-19 impacted high school students' choice and interest in pursuing an engineering degree. While COVID-19 impact on educational experience was found to affect self-efficacy, there was no relationship between self-efficacy and students' ability to develop support networks within their departments or outside their campus. While the two campuses studied did not interpret those questions similarly, it ultimately did not influence the relationship between networking and self-efficacy. This could be due to our sample, which included college students at varying stages of their academic careers rather than early career engineers.

7. Conclusions and Future Research

In this study, students who reported a more positive COVID-19 educational experience had higher engineering self-efficacy scores, which in turn resulted in higher intentions to persist in their engineering major. Conversely, as a student perceived their educational experiences during COVID-19 to be more negative, their engineering self-efficacy was more likely to decrease, which resulted in their being less likely to intend to persist in their engineering degree. Further, our survey results show this impact of COVID-19 on self-efficacy and persistence intentions was similarly experienced by students at both a Hispanic Serving Institute and a Historically Black College/University.

This study may foreshadow a much larger problem as the effects of COVID-19 are likely to be long-term. The extent of COVID-19's impact on education is just beginning to be studied. The students in this study had already selected engineering as their career path. Thus, as illustrated in this study, students who perceived a negative education experience because of COVID-19 were less likely to intend to persist. What is unknown is to what degree negative educational experiences of high school or middle school students during COVID-19 will discourage students from pursuing engineering careers. If the pattern we observed with college students holds true for younger students, this may presage a much larger problem and will need to be closely monitored at all levels of education over the next few years.

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