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Impact of COVID-19 Transition to Remote Learning on Engineering Self-efficacy and Outcome Expectations

Johanna Milord, University of Missouri - Columbia

Johanna Milord is a Counseling Psychology Doctoral Candidate at the University of Missouri. She earned her Masters of Science degree in Mental Health Counseling. Her general research focus is marginalized populations' attainment of their desired academic and career outcomes. Her most recent projects have explored career self-efficacy and critical race consciousness interventions.

Fan Yu, University of Missouri - Columbia
Dr. Sarah Lynn Orton P.E., University of Missouri - Columbia

Dr. Orton is an associate professor in Civil Engineering and is an active member of the American Concrete Institute and the American Society of Civil Engineers. Dr. Orton also serves as the Director of Undergraduate Studies for the Civil and Environmental Engineering Department at the University of Missouri. She has participated in several programs aimed at improving undergraduate education. Her research projects have involved the use of carbon fiber reinforced polymers to strengthen structures, analysis and testing for reinforced concrete frames under disproportionate collapse, and risk and reliability analysis of bridges and offshore structures. She is a registered professional engineer in Missouri.

Dr. Lisa Y. Flores, University of Missouri - Columbia

Lisa Y. Flores, Ph.D. is a Professor of Counseling Psychology at the University of Missouri. She has expertise in the career development of Latino/as and Latino/a immigrant issues and has 80 peer reviewed journal publications, 19 book chapters, and 1 co-edited book and presented over 200 conference presentations in these areas. She has been PI and co-PI on grants funded by NSF and USDA to support her research. She is Editor of the Journal of Career Development and past Associate Editor of the Journal of Counseling Psychology, and has served on the Editorial Boards of the Journal of Vocational Behavior, The Counseling Psychologist, Journal of Counseling Psychology, and Career Development Quarterly.

Rose M. Marra, University of Missouri - Columbia

Professor Rose M. Marra is the Director of the School of Information Science and Learning Technology at the University of Missouri. She is PI of the NSF-funded Supporting Collaboration in Engineering Education, and has studied and published on engineering education, women and minorities in STEM, online learning and assessment. Marra holds a PhD. in Educational Leadership and Innovation and worked as a software engineer before entering academe.

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INTRODUCTION

The outbreak of the coronavirus in Spring 2020 and resulting widespread health and safety measures resulted in a considerable shift in how teaching was delivered across the United States (U.S.). The sudden transition to remote learning brought about several changes and challenges particularly to college and university campuses. This paper evaluates the impact of the transition of college engineering courses from in-person instruction to emergency remote learning on students' social cognitions of engineering-related self-efficacy and outcome expectations. Prior research indicates that these social cognitions are significant predictors of STEM choice goals and actions [1]. Our unique data set measures students' social cognitions over the course of the Spring 2020 semester in a set of 8 engineering courses using the same group of students before and after the unexpected transition to remote learning.

BACKGROUND

This study seeks to determine if the sudden transition to remote learning impacted students' engineering self-efficacy and outcome expectations. If these social cognitions were impacted, then student's performance, persistence, and approach/avoidance behavior may also be impacted. To understand the basis of the study, the following section reviews the relevant background on social cognitions.

Social Cognitions
Bandura's [2, 3] social cognitive theory postulates that the social cognitions of self-efficacy and outcome expectations are the key mechanisms through which individuals engage in and persist in behaviors. This theory is central to Social Cognitive Career Theory (SCCT) [4], which consists of three interlocking models that explain the development of career-related interests, choice goals, actions and performance, as shown in Figure 1. SCCTs core components include the variables of self-efficacy (i.e., confidence in one's ability to successfully perform a domain-specific task), outcome expectations (i.e., anticipated outcomes of a particular behavior), interests (i.e., patterns of likes and dislikes for career activities), and goals (i.e., determination for a particular activity or outcome). SCCT assumes that the four learning experiences (i.e., performance accomplishments, vicarious learning, social persuasion, and emotional arousal) help to shape self-efficacy beliefs and inform outcome expectations. A recent meta-analysis indicated that the four learning experiences accounted for significant variance in STEM self-efficacy and outcome expectations [5]. Prior meta-analyses demonstrated that these social cognitions in turn, shape STEM interests and career choice goals [1], and self-efficacy beliefs accounted for significant variance in students' academic performance and academic persistence [6, 7].

Self-Efficacy
Self-efficacy, introduced by Bandura [2, 3] refers to an individual's belief in their ability to plan and complete a specific task and is hypothesized to determine whether someone will avoid or approach certain career options, the quality of performance, and their persistence when faced with obstacles [8]. Self-efficacy has also been found to be more indicative of successful

completion of tasks than actual skill level [9]. Self-efficacy is not a trait concept (that is, a concept that remains relatively static), but it is a cognitive appraisal of judgement of future performance capabilities within a specific domain [10]. As such, it must be domain specific and measured against behavior within a specific area. In this study, we assess self-efficacy in the engineering domain.

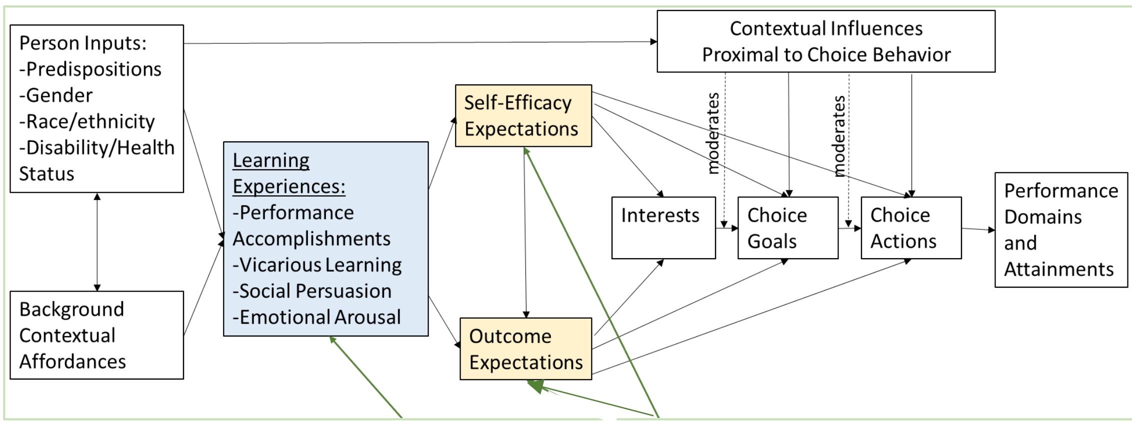

Figure 1: Adapted Figure of Self-Efficacy and SCCT Model [4]

As illustrated in Figure 1, "self-efficacy expectations" is influenced by the four domain areas of: performance accomplishments, vicarious learning, social or verbal persuasion, and emotional arousal [4, 11]. *Performance accomplishments or "mastery of experiences"* are believed to be a major source of self-efficacy beliefs. They are past direct experiences that demonstrate to a person that they are able to successfully perform a future task (i.e., if you have done it before and performed well, you can do it again). High self-efficacy evolves from success in past experiences and low self-efficacy from failures at activities within the given domain. *Vicarious experiences* are observations of others successfully completing a task (i.e., if they can do it, so can I). However, since observing is not a direct reflection on one's one skill it is believed to have a weaker influence on self-efficacy beliefs relative to other sources. *Social persuasion* is encouragement from others. It can take the form of either positive encouragement to perform a task which will increase self-efficacy or negative discouragement often in the form of discrimination and bias that will decrease self-efficacy. Finally, *emotional arousal* is the emotion generated around performing the task. Although they can be positive, they often take the form of anxiety or fear about a given task. This anxiety has been shown to be driven by the stereotype threat [12] in which members of a group for which there is a negative stereotype may experience performance anxiety.

A meta-analysis of 28 studies (61 samples) by Byars-Winston et al. found that the four sources explained a significant proportion of variance (22%) of STEM self-efficacy [13]. Another meta-analysis of 104 STEM studies (141 independent samples) found that the four sources explained significant variance in self-efficacy (36%) [5].

Outcome Expectations

Although self-efficacy has received the most research attention in Bandura's [3] social cognitive theory, outcome expectations are also believed to serve a unique role in driving behaviors and is also illustrated in figure 1. Outcome expectations refer to the expected outcomes for engaging in a particular behavior, and can include positive, negative, or neutral anticipated consequences. Bandura [3] identified categories of outcome expectations to include social, material, and self-evaluative outcomes. Bandura hypothesizes that outcome expectations are determined by self-efficacy beliefs, as people will expect positive outcomes for activities that they possess strong self-efficacy. Sheu and colleagues' meta-analysis of 104 STEM studies found that the four sources explained 42% of the variance in outcome expectations [5].

Engineering Career Success and Social Cognitions
Prior studies confirm the relationship between self-efficacy beliefs and decisions around pursuing or persisting in careers such as in engineering [14,15]. The importance of self-efficacy is reinforced for success in engineering. Thus, attending to the development of students' self-efficacy and outcome expectations may support engineering student's persistence in the field. Engineering persistence is defined as an individual staying in their engineering major or continuing to pursue the engineering degree [16]. In this study, we assess if self-efficacy and outcome expectations were impacted by the transition to remote learning.

Online Learning Modes: Emergency Remote vs Distance Learning

> Terminology: for the purposes of this paper, "online" or "distance" learning modes will refer to courses that were conceptually designed to be delivered in an online, virtual format. On the other hand, "emergency remote" or "remote" learning will refer to courses that were structurally created for in-person delivery and transitioned to online learning formats due to various reasons. These "emergency remote" courses are adapted temporarily and will return to their original format once the urgent situation has decreased [17].

Typically, research on the effectiveness of online learning on students' outcomes has had mixed results. Literature suggests that online learning may be an effective mode for learning when certain elements are intact. Jaggars and Bailey [18] summarized and responded to a meta-analysis conducted by the U.S. Department of Education (DOE). Initial DOE data suggested that learning outcomes from online instruction were stronger than face-to-face instruction. The DOE results however, pertained to well-prepared university students. Data outside of the meta-analyses indicates that without additional supports, traditionally underrepresented student populations in online education may not achieve results that are comparable to their peer counterparts. Neuhauser [19] found no significant differences between the same college course delivered asynchronously online, as compared to face-to-face when evaluated across gender, age, learning preferences, familiarity with media, course effectiveness, and test grades. Another meta-analysis [20] evaluated 45 studies contrasting fully or partial (blended) online instruction with face-to-face instruction and abstracted 50 independent effect sizes. Most sample sizes were modest and covered a range of course topics in science, math, and the social sciences. The results found 11 studies were significantly positive favoring online learning and 3 significant negative effects favoring face-to-face instruction.

More recent literature celebrates online learning's benefit with flexibility in schedule and accessibility. A recent literature review [21] indicated that structured online discussions with clear guidelines, well-designed courses with interactive content and flexible deadlines, involvement from the educator and personalized, timely feedback foster healthy online learning environments. Even so, students with poor internet access or who are new to virtual education altogether may be subject to great difficulties in online learning [22].

While data have shown that online learning can be effective, it is important to highlight the unique factors around the COVID -19 transitions to remote education styles. Research that supports efficacy of online education [19, 20, 21] highlights important features such as teacher preparedness, clear guidelines, and structured coursework. These online courses typically are arranged in advance with planning and thorough organization about six to nine months before the course is delivered [17]. Another study found that aspects of online education that are integral to learning virtually include staff's readiness and confidence, student accessibility and student motivation [23].

This past March 2020, Universities across the U.S. experienced an emergency shift to remote teaching almost overnight [24]. This sudden shift caused courses designed for face-to-face instruction to be moved online for "remote learning" experiences due to the global pandemic. Students and instructors were placed in an unlikely scenario of having to teach their classes through technology and internet resources with little to no preparation and in the instructor's case, often no training. Universities asked instructors to quickly convert their courses to a learning management system (LMS) (i.e. Canvas, Blackboard, etc..) and to utilize new approaches to deliver of course content in a remote, online setting. At universities across the U.S., courses were delivered asynchronously (through recorded lecture presentation or PowerPoint slides with voiceovers) or through synchronous meetings using portals such as Zoom, Microsoft Teams or Google Meet. Instructors in the engineering field specifically, struggled with physical representations and tools for learning such as translating diagram designs and mathematical models to online means. Natural supports of study groups, peer review, and conversational support also became limited or non-existent during COVID -19 emergency social distancing protocols and closing of school face-to-face instruction.

Research completed in the first few months following COVID -19 explored how transitions to online learning on a full scale were difficult for most education systems, including the most "high performing" education systems. Challenges ranged from infrastructure costs, to supporting teachers in offering "high quality, curriculum-relevant digital learning content and assessment tools" [22]. Schools that had pre-existing widespread online learning programs, good education systems and were generally in well-resourced affluent areas were more able to accommodate abrupt shifts to remote learning. Some studies indicate that academic performance may dip in the short-term as students acclimate to new online systems, or it may be difficult to maintain motivation for long-term online learning beyond a few months. A recent study for online college courses [25] highlighted additional barriers that students faced such as decreased motivation and anxiety, and distractions.

According to other scholars that collected data during the time of transition in Spring 2020, the shift online had several challenges; however, instructor actions such as setting clear learning outcomes, modifying exam formats, reducing assignment numbers, and allowing for more flexible self-paced timing assisted students [26, 27, 28, 29]. Despite the possibilities of negatives of online learning such as technical difficulties, internet issues, or difficulty logging in [23], there are a number of solutions as well. Adjustment for students' educational outcomes, modifying content, pacing, interaction models, and assessment needed to be adapted to ensure student's success.

Impact of Instructional Changes on University Student Climate

Findings from a student survey [30] at the conclusion of the Spring 2020 semester at the institution where this study was conducted indicated that about 57% of respondents rated online recorded lectures as highly or mostly effective while about 38% of engineering students felt that class sessions by Zoom were highly or mostly effective. Although about 55% reported that instructors needed to be more flexible with challenges facing students, 56% of engineering students thought their instructor's efforts to teach remotely was good or better than they thought it would be.

Students provided additional feedback around desiring more flexible schedules with online learning and increased mental health concerns. These responses illustrated students' concerns about instructors' abilities to transition smoothly and beliefs that more support for instructors was needed. The report also indicated that several students felt the quality of their education was suffering with online classes.

Present Study

The present study tracks engineering students' social cognitions in Spring 2020, when courses were forced to pivot to online learning due to the global pandemic. The study evaluates social cognitions at the start of the semester, at midterm, and at the end of the semester. Our research contributes to the body of existing literature on the impact of the COVID-19 transitions and explores differences across gender groups and various engineering course subjects.

METHOD

Research Design

For this study, we gathered data during the 16-week spring semester of 2020. We used a pre-mid-post design to administer a student survey at 3 time points that included a set of measures (described further below). Time 1 was administered within the first two weeks of the semester, Time 2 was administered during weeks 8 and 9 shortly after the COVID-19 shutdown and transition to remote learning, and Time 3 was administered during the final two weeks of the semester. The quantitative data in our research utilized Qualtrics survey scores. Furthermore, qualitative data from open-ended questions were included in our study and used to describe the students experiences' in their respective courses.

Participants

Participants consisted of students enrolled in engineering courses at a public land grant university in the Midwest. A total of 224 participants completed the Time 1 survey, 190 participants completed the Time 2 survey, and 101 participants completed the Time 3 survey. To maintain a consistent sample for comparisons, we retained participants who completed surveys at any two comparison points. See Table 1 (below) for the number of participants at each comparison point. We also included demographic descriptions of the participants in Table 2 below. Most (89%) of the participants self-identified as White, or European American, and almost 80% were men. The participants' mean ages varied across the 3 time points generally from 20 to 22. We collected data from eight required engineering courses and the instructors of these courses participated in a faculty learning community during the semester. See Table 3 for a list of participating courses and the instructional model when courses switched to remote education styles after the transition. Based on Table 3, participating engineering courses were either at traditional sophomore, junior and senior levels. Consequently, as demonstrated in Table 2, most participating students are mid-level in their academics with fewer being from their first-year. Only 3 of the 8 courses provided enough matched participants for the data analysis for this study: courses 1, 2, and 3.

Table 1: Sample Size for Each Comparison Point

	Time 1 vs Time 2	**Time 2 vs Time 3**	**Time1 vs Time 3**
Sample Size	98	67	57
Mean of Age	20.94	21.63	21.28

Table 2: Frequency and Proportion of Race, Gender, Class Standing and Participating Course

Item		**Time 1 vs Time 2**		**Time 1 vs Time 3**		**Time 2 vs Time 3**	
		N	**%**	**N**	**%**	**N**	**%**
Race	White/European American	88	89.8	51	89.5	60	89.6
	Black/African American	2	2.0	1	1.8	2	3.0
	Latinx/Hispanic	2	2.0	0	0	0	0
	Asian/Asian American	4	4.1	3	5.3	3	4.5
	Native American	0	0	0	0	0	0
	Biracial/Multiracial	1	1.0	2	3.5	2	3.0
	Other	1	1.0	0	0	0	0
Gender	Woman	21	21.4	14	24.6	14	20.9
	Man	77	78.6	43	75.4	53	79.1
Class Standing	First-Year	8	8.2	2	3.5	4	6.0
	Sophomore	38	38.8	22	38.6	24	35.8
	Junior	32	32.7	22	38.6	26	38.8
	Senior	15	15.3	10	17.5	12	17.9
	Other	5	5.1	1	1.8	1	1.5

Table 3: Participating courses

	Course Level /Department	Instructional Model after transition	Enroll -ment	Time 1 vs Time 2	Time 1 vs Time 3	Time 2 vs Time 3
Course 1	Sophomore /Engineering	synchronous	123	41	19	26
Course 2	Junior /Civil	synchronous	31	16	14	17
Course 3	Junior /Civil	synchronous	37	25	12	8
Course 4	Junior / Mechanical	asynchronous	22	<3	<3	<3
Course 5	Sophomore / Information Technology	asynchronous	39	<3	<3	<3
Course 6	Junior /Chemical	asynchronous	25	6	6	3
Course 7	Junior /Industrial	asynchronous	35	4	3	<3
Course 8	Senior /Chemical	synchronous first, then asynchronous	14	<3	<3	3

Measures

We assessed **engineering self-efficacy** with two measures [31, 32]. The scale by Lent and colleagues "Engineering Self-Efficacy Scale 1, or ESES1" included 4 items in which participants responded using a 10-point Likert scale ranging from "No Confidence at all" (0) to "Complete Confidence" (9). Participants rated their confidence in their ability to perform well in courses. Sample items include, "complete all of the 'basic science' requirements for your engineering major with grades of B or better" and "excel in your engineering major over the next semester." The other scale by Fantz and colleagues "Engineering Self-Efficacy Scale 2 or ESES2" included 9 items, with an 8-point Likert scale that ranged from "Strongly Disagree" (0) to "Strongly Agree" (7). Sample items include, "I'm confident I can understand the basic concepts in my engineering classes" and "I'm certain I can master the skills being taught in my engineering classes." Prior research indicated that ESES1 scores were related with measures of theoretical-consistent constructs and yielded adequate internal consistency reliability estimates (α = .84 to .92) [31, 32, 33, 34] provided support for the internal consistency reliability of ESES2 items (α = .83 to .88) and provided evidence that scores were valid.

We assessed both **positive and negative outcome expectations in engineering** with two separate measures. The Engineering Positive Outcome Expectations Scale (EPOES) [33] included 10 items that participants responded to using a 10-point Likert scale, ranging from "Strongly Disagree" (0) to "Strongly Agree" (9). Sample items included, "Graduating with a BS degree in engineering will likely allow me to receive a good job offer" and "Graduating with a BS degree in engineering will likely allow me to earn an attractive salary." Scores on this measure yielded adequate internal consistency reliability (α = .87 to .89) and were related to scores on theoretically consistent measures [31, 33, 34]. The Engineering Negative Outcome Expectations Scale (ENOES) [36] was a 21-item measure, to which participants responded using a 10-point Likert scale that ranged from "Strongly Disagree" (0) to "Strongly Agree" (9). Sample items included "Being employed as an engineer will likely result in being less attractive to my partner" and "Being employed as an engineer will likely result in challenges balancing between work responsibilities and family obligations." Lee and colleagues [36] reported a strong reliability (α = .94) for scores on this measure, and scores were negatively correlated to engineering academic satisfaction, environmental supports, intended persistence, engineering self-efficacy, and engineering positive outcome expectations.

Finally, a 4-item scale was used to assess **engineering persistence intentions** (EPIS) [35]. Participants responded to the items (e.g., "I intend to major in an engineering field" and "I plan to remain enrolled in an engineering major over the next semester") using a 5-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). Internal consistency estimates ranged from .89 to .95 in prior studies with engineering student samples, and scores were significantly related to scores of theoretically-consistent measures [31, 33, 34].

Additionally, open-end questionnaires were included at Time 2 to explore students' concern about moving the class online. There were 173 participants that answered the questions "What concerns do you have about moving this class online? (Q1)" and 165 participants answering the questions "What challenges do you anticipate encountering in online learning in this class? (Q2)" At Time 3, 101 students answered the question, "Did your motivation for learning in this class change after the class moved online? (Q3)".

Data Collection

The data were collected during the spring semester of 2020 over three time points: Time 1, Time 2 and Time 3, and at each of the 3 time points, participants were required to complete a survey including two or three section parts:

Section 1) Demographic questionnaire (e.g., gender, race, major, and educational level)
Section 2) A survey combining four instruments collecting the quantitative data by assessing participants' engineering self-efficacy, positive and negative outcome expectations in engineering, and engineering persistence intentions
Section 3) For Time 2 and Time 3, participants were invited to answer an open-ended questionnaire in order to better understand their online learning experiences

Researchers administered the surveys, which included measures of self-efficacy, outcome expectations, persistence intentions and a demographic survey. At Time 1, the paper survey was distributed in each of the course classrooms, and participants completed the survey using pen and paper. Due to emergency remote instruction, Qualtrics, an online survey program, was used to administer the Time 2 and Time 3 surveys.

Data Analysis

Quantitative data were entered and analyzed using the RStudio and Microsoft Excel software. RStudio was used to congregate the data when participants were counted multiple times for completing surveys at different timepoints. Demographic data were calculated in Microsoft Excel software including means and standard deviations of age, the frequency and proportion of race, gender, and class standing. RStudio was used to run a series of paired sample T-tests to compare if there was a significant difference between the responses across the study's variables from Time 1 to Time 2, from Time 2 to Time 3, and from Time 1 to Time 3.

For qualitative data, a software named NVIVO was used to count the word frequency. A group includes the stemmed words. For example, the frequency of words "material" includes the frequency of "material" and "materials". The frequency of students' motivation was calculated by Excel.

RESULTS

Quantitative Data

The means and standard deviations of the scores for each of the measured variables at each time point are shown in Table 4 below. The results showed a slight increase in the mean scores on the engineering self-efficacy (ESES1 and ESES2) and positive outcome expectation (EPOES) measures through the semester while persistence intentions (EPIS) and negative outcome expectations (ENOPES) saw little to no change. Figure 1 demonstrates the trend through the Spring 2020 semester for each of the measured variables. While it is to be expected that self-efficacy and outcome expectations will increase as a student learns material in a course, the data shows that despite the disruption in instructional delivery mode from face-to-face to remote teaching, increases were still seen.

Table 4: Descriptive Statistics for the Study's Main Variables for the Full Sample

TIME POINT	**Time 1**		**Time 2**		**Time 3**	
Sample Size	224		190		101	
Instruments	**M**	**SD**	**M**	**SD**	**M**	**SD**
ESES1 - Engineering Self-efficacy [31]	6.70	1.46	6.99	1.79	7.21	1.51
ESES2 - Engineering Self-Efficacy [32]	5.12	1.21	5.23	1.42	5.39	1.42
EPOES - Engineering Positive Outcome Expectations [35]	7.08	1.64	7.22	1.65	7.23	1.63
EPIS - Engineering Persistence Intentions [35]	4.78	0.5	4.78	0.55	4.77	0.49
ENOPES - Engineering Negative Outcome Expectations Scale [36]	2.89	2.36	3.11	2.65	2.75	2.42

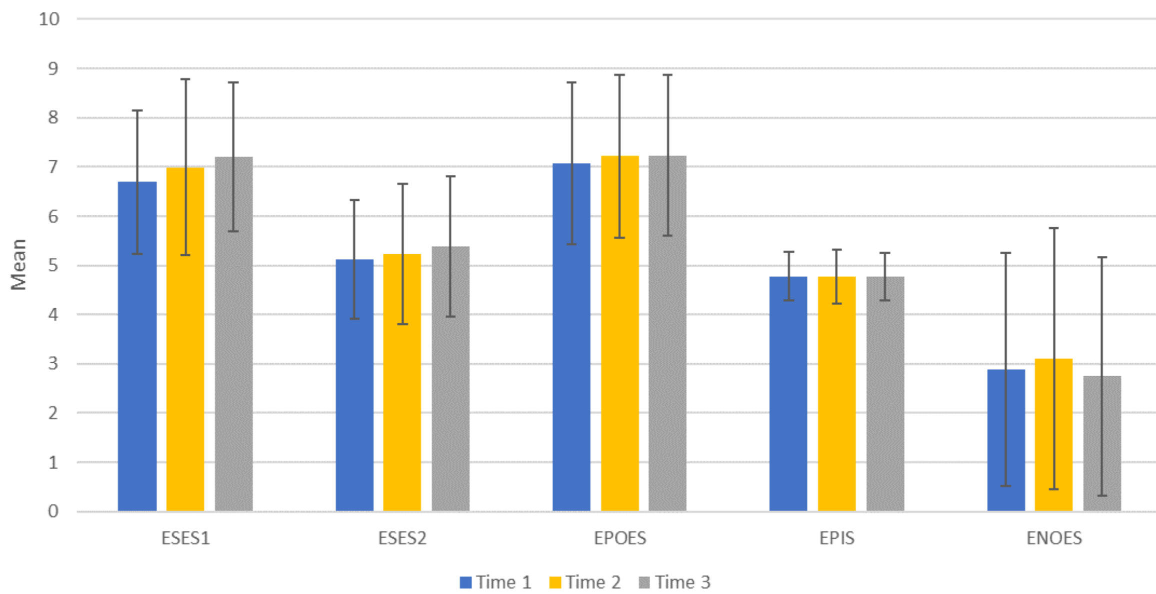

Figure 2: Trend of Mean Scores for Each Measure

Table 5 below presents findings from a series of paired sample t-tests to analyze differences between scores on the study's measures from Time 1 to Time 2, Time 1 to Time 3, and Time 2 to Time 3. Findings indicate a statistically significant increase in both measures of engineering self-efficacy (ESES1, ESES2) from Time 1 to Time 3 ($p < 0.01$; $p < 0.5$), but no statistically significant difference at the other time points. No statistically significant differences were found for scores on the other measures at the various time point comparisons.

Table 5: Overall Results of Paired T-tests for Overlapped Data

	Time 1 vs Time 2				**Time 1 vs Time 3**				**Time 2 vs Time 3**			
Sample Size	98				57				67			
Instrument	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**
ESES1	1	6.89	2.58	0.485	1	6.89	1.23	** <0.01	2	6.91	1.17	0.156
	2	7.07	1.28		3	7.44	1.26		3	7.15	1.47	
ESES2	1	5.16	1	0.120	1	5.26	0.93	*0.011	2	5.11	0.96	0.192
	2	5.34	1.02		3	5.64	1.10		3	5.31	1.31	
EPOES	1	7.2	1.13	0.644	1	7.05	1.41	0.114	2	7.30	1.13	0.617
	2	7.25	1.14		3	7.35	1.15		3	7.24	1.12	
EPIS	1	4.48	0.34	0.577	1	4.86	0.35	0.083	2	4.69	0.35	0.609
	2	4.86	0.29		3	4.77	0.40		3	4.67	0.43	
ENOES	1	2.62	1.26	0.644	1	2.88	1.34	0.289	2	3.05	1.79	0.157
	2	2.76	1.6		3	2.70	1.70		3	2.81	1.51	

Note. ns $p > 0.05$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$, **** $p \leq 0.0001$

Next, we compared students' scores on the measures assessing engineering self-efficacy, positive and negative outcome expectations and persistence intentions across gender groups (Table 6 and

Table 7). After running analyses for each gender group separately, the results of a series of paired sample t-tests indicated an increase in engineering self-efficacy scores (ESES1, ESES2) among men students from Time 1 to Time 3 ($p < 0.05$; $p < 0.01$) which is similar to the overall results (Table 6). However, an increase of engineering self-efficacy scores was only found on the ESES1 instrument among women students during the Spring 2020 semester ($p < 0.05$) and there was a small sample size ($n = 14$). See Table 7 for details.

Table 6: Results of Paired Sample t-tests Among Male Students

	Time 1 vs Time 2				**Time 1 vs Time 3**				**Time 2 vs Time 3**			
Sample Size	77				43				53			
Instrument	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**
ESES1	1	6.70	1.54	0.007	1	6.91	1.29	*0. 011	2	7.15	1.02	0.615
	2	7.14	1.26		3	7.48	1.36		3	7.25	1.51	
ESES2	1	5.26	0.91	0.315	1	5.30	1.00	** <0.01	2	5.26	0.89	0.285
	2	5.37	0.88		3	5.71	0.94		3	5.44	1.13	
EPOES	1	7.27	1.04	0.535	1	7.13	1.46	0.183	2	7.31	1.11	0.889
	2	7.21	1.15		3	7.44	1.11		3	7.29	1.12	
EPIS	1	4.86	0.31	0.720	1	4.88	0.30	0.103	2	4.75	0.30	0.485
	2	4.87	0.28		3	4.79	0.38		3	4.71	0.40	
ENOES	1	2.57	1.31	0.647	1	2.95	1.34	0.200	2	2.86	1.81	0.358
	2	2.64	1.62		3	2.67	1.77		3	2.68	1.56	

Note. ns $p > 0.05$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$, **** $p \leq 0.0001$

Table 7: Results of Paired t-tests Among Female Students

	Time 1 vs Time 2				**Time 1 vs Time 3**				**Time 2 vs Time 3**			
Sample Size	21				14				14			
Instrument	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**
ESES1	1	7.58	4.76	0.450	1	6.82	1.04	*0.044	2	5.99	1.28	0.020
	2	6.8	1.3		3	7.34	0.93		3	6.77	1.26	
ESES2	1	4.77	1.22	0.243	1	5.16	0.68	0.480	2	4.52	1.01	0.474
	2	5.25	1.44		3	5.41	1.52		3	4.81	1.78	
EPOES	1	6.95	1.43	0.079	1	6.81	1.25	0.355	2	7.26	1.23	0.462
	2	7.4.	1.11		3	7.05	1.24		3	7.04	1.16	
EPIS	1	4.77	0.41	0.620	1	4.77	0.46		2	4.49	0.45	0.947
	2	4.81	0.33		3	4.71	0.49	0.583	3	4.50	0.49	
ENOES	1	2.79	1.06	0.093	1	2.69	1.38	0.576	2	3.76	1.56	0.103
	2	3.21	1.44		3	2.81	1.53		3	3.33	1.22	

Note. ns $p > 0.05$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$, **** $p \leq 0.0001$

Finally, we analyzed changes in scores across courses. We selected the courses where a relatively large amount of the total number of students completed the surveys.

In course 1, results of a series of paired sample t-tests indicated a significant increase of engineering self-efficacy scores on both measures (ESES1, ESES2) among participants in this class from Time 1 to Time 3 ($p < 0.05$; $p < 0.05$) (see Table 8) which again is similar to the overall results described in Table 5.

Table 8: Results of Paired Sample t-tests among Students in Course 1

	Time 1 vs Time 2				**Time 1 vs Time 3**				**Time 2 vs Time 3**			
Sample Size	41				19				26			
Instrument	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**
ESES1	1	7.34	3.57	0.775	1	6.54	1.09	*0.043	2	6.90	1.34	0.8753
	2	7.18	1.26		3	7.17	1.11		3	6.95	1.60	
ESES2	1	5.24	1.14	0.369	1	5.07	0.53	*0.014	2	5.04	1.05	0.5759
	2	5.43	1.09		3	5.66	1.07		3	5.21	1.55	
EPOES	1	7.42	1.15	0.919	1	6.85	1.78	0.174	2	7.36	1.27	0.5271
	2	7.4	1.18		3	7.49	1.16		3	7.19	1.28	
EPIS	1	4.8	0.36	0.357	1	4.75	0.45	0.320	2	4.64	0.35	0.3642
	2	4.86	0.27		3	4.66	0.49		3	4.55	0.50	
ENOES	1	2.31	1.41	0.078	1	2.84	1.39	0.799	2	3.60	2.29	0.2455
	2	2.71	1.84		3	2.90	1.71		3	3.15	1.54	

Note. ns $p > 0.05$, *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$, **** $p \leq 0.0001$

In course 2, results of a series of paired sample t-tests indicated a significant increase in scores on one of the engineering self-efficacy measures (ESES1) from Time 1 to Time 3 ($p < 0.05$) and from Time 1 to Time 2 ($p < 0.05$) (see Table 9). Additionally, a significant increase was found in the (ESES2) measure from Time 2 to Time 3. This is slightly different than the overall results in Table 3.

Table 9: Results of Paired Sample T-tests among Students in Course 2

	Time 1 vs Time 2				Time 1 vs Time 3				Time 2 vs Time 3			
Sample Size	16				14				17			
Instrument	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**
ESES1	1	6.14	1.79	*0.015	1	6.93	1.39	*0.012	2	6.97	0.98	0.175
	2	7.23	1.04		3	7.86	1.33		3	7.18	1.34	
ESES2	1	5.17	0.93	0.872	1	5.56	1.18	0.308	2	4.83	0.96	*0.018
	2	5.22	0.94		3	5.78	0.97		3	5.26	0.93	
EPOES	1	7.28	1.39	0.495	1	7.24	1.44	0.296	2	7.44	1.04	0.493
	2	7.41	1.22		3	7.59	1.12		3	7.52	0.98	
EPIS	1	4.8	0.36	0.718	1	4.93	0.18	0.427	2	4.67	0.33	0.811
	2	4.78	0.38		3	4.93	0.18		3	4.69	1.35	
ENOES	1	2.8	1.25	0.914	1	2.62	1.18	0.221	2	2.51	1.37	0.755
	2	2.77	1.84		3	2.20	2.07		3	2.45	1.74	

Note. ns $p > 0.05$, $*p \leq 0.05$, $**p \leq 0.01$, $***p \leq 0.001$, $****\ p \leq 0.0001$

For course 3, results of a series of paired sample t-tests indicated a statistically significant increase in scores on one of the two engineering self-efficacy measures (ESES1) in course 3 from Time 1 to Time 3 ($p < 0.05$) as well as a statistically significant decrease in engineering persistence intentions scores from Time 1 to Time 3 ($p < 0.05$) (see Table 10). This is somewhat different from the overall results which did not see a decrease in the persistence intensions.

Table 10: Results of Paired Sample T-tests among Students in Course 3

	Time 1 vs Time 2				Time 1 vs Time 3				Time 2 vs Time 3
Sample Size	25				12				8
Instrument	**Time Point**	**M**	**SD**	**p-value**	**Time Point**	**M**	**SD**	**p-value**	Limited Sample Size
ESES1	1	6.66	1.44	0.217	1	7.15	1.36	*0.047	
	2	6.93	1.06		3	8.06	1.14		
ESES2	1	5.05	0.9	0.963	1	5.31	1.21	0.444	
	2	5.06	0.81		3	5.60	1.23		
EPOES	1	6.79	0.84	0.963	1	6.98	0.88	0.464	
	2	6.91	0.85		3	7.17	1.04		
EPIS	1	4.87	0.32	0.900	1	4.98	0.07	*0.028	
	2	4.86	0.3		3	4.65	0.48		
ENOES	1	2.98	0.81	0.460	1	2.91	0.86	0.731	
	2	2.82	1.2		3	2.76	1.73		

Note. ns $p > 0.05$, $*p \leq 0.05$, $**p \leq 0.01$, $***p \leq 0.001$, $****\ p \leq 0.0001$

Qualitative Data
Based on the data collected at Time 2, the most frequently used words included “difficult”, “works”, “material”, “help”, and “lectures”. Later, at Time 3 near the end of the semester, we asked students “Did your motivation for learning in this class change after the class moved online?” Most of the students (69%, $n = 70$) indicated that their motivation decreased, whereas 27% ($n = 27$) reported that their motivation stayed the same, and a mere 4% ($n = 4$) indicated that their motivation for learning increased after the transition to online learning.

DISSCUSION and CONCLUSIONS

Data were collected from eight different engineering courses. All courses started as in-person and transitioned to asynchronous, synchronous or a hybrid partway through the 16-week semester.

Results demonstrated a statistically significant increase in engineering self-efficacy scores on the two utilized measures between Time 1 and Time 3 but not between the other time points in the overall results. Although the increase was statistically significant ($p < 0.01$; $p < 0.5$) the magnitude of the increase was marginal (only 7%-8% increase in the mean score). When separated by gender, women only had a significant increase in engineering self-efficacy on one measure while men maintained a significant increase on both self-efficacy measures. When separated by course, different courses showed slightly different trends on which measures and which time points showed a statistically significant increase and for one course, engineering persistence intentions significantly decreased from Time 1 to the semester’s end at Time 3, indicating that the course content and delivery method may affect students’ persistence intentions.

Results suggested that despite the sudden change in instructional mode (from in-classroom to remote), students’ perceptions of positive and negative outcome expectations and persistence intentions did not change greatly. In fact, students’ engineering persistence was not significantly impacted across the eight courses and on the contrary, engineering self-efficacy statistically increased for both genders and across the data consistently. This suggests that despite the abrupt transition online to remote education, students increased in their confidence in their ability to succeed in their engineering coursework (self-efficacy), and for the most part still intend to major and find employment in engineering (persistence). However, qualitative data highlights that the majority (69%) of these student’s felt that their motivation decreased, whereas about a quarter (27%) felt as if their motivation stayed the same.

The students’ outcome expectations remained the same, but motivation changed. Students typical learning strategies may have been employed as well and helped to increase self-efficacy as the semester continued. Research hints that perhaps motivation came from a need for health and science professionals amid the pandemic [37] . These conflicts may be further explored in future studies.

There are mixed results in the current literature about student’s academic performance after learning transitioned to emergency remote classroom instruction post- COVID -19. Some recent studies [27, 37] from Spring 2020 found little differences in student outcomes and others [22] reported difficult challenges and obstacles. Our findings seem to be in-line with the existing literature on remote learning after COVID -19. While students still seemed to struggle with shifts in exam and lecture formats, inconsistent access to internet, access to instructors, lack of social support via peers, and several more difficulties, not all challenges were reflected in their social cognitions. One study specifically looking at undergraduate students with a higher risk of dropping out found they had mixed feelings on persisting to work, though no "massive" drop in motivation was evident [37].

Institutional leadership at universities, professors and students alike, all demonstrated a certain amount of resilience, flexibility and adaptation this past spring. Instructor's modifications to course curriculum and student's willingness to use asynchronous or learning management systems created learning environments that tried to minimize academic disruption as much as possible.

Limitations

One important limitation to note is the time frame for data collection that captures a unique, and briefly fluctuating span of time. More consistent and long-term data collection after the pandemic is recommended to better understand the course transition period. While we found that in the interrupted Spring 2020 semester, self-efficacy did increase, these results need to be compared to the expected increase in a typical semester to understand how social cognitions were impacted by the interruption. Another limitation is that our sample of engineering courses varied in terms of enrollment, pre-pivot teaching methods (e.g. lecture, problem solving), and teacher experiences. Our sample was not large enough to disaggregate by these factors, but we recognize that these may influence our current results. Our sample can also significantly benefit from being more diverse in gender, race, class and other factors.

Conclusion

A sudden transition to remote learning in Spring 2020 caused unprecedented shifts in learning for college engineering students. Teachers, administrators and students alike had to make unplanned, swift adjustments to course curriculum to transition lesson plans remotely after social distancing guidelines due to COVID -19 limited in-person interactions. Social cognitive theory supports how social cognitions of self-efficacy and outcome expectations influence academic performance, persistence and career choice goals. This study was conducted during a unique timeframe where time 1 data observed students at the beginning of a planned typical semester, time 2 was shortly after the abrupt transition to remote learning and time 3 captured the end of a fully remote learning environment. The data showed that despite the sudden change in instructional mode (from in-classroom to remote), students' perceptions of positive and negative outcome expectations and persistence intentions did not change greatly. The data demonstrates how social cognitions were impacted throughout the Spring 2020 semester at a university in the Midwest and how they can benefit engineering education as a whole when combined with the broader research base that is currently being developed nation-wide by the COVID-necessitated pivot to online learning.

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