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Value and Interest: Do They Really Make a Difference in Student Engagement

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Can I do Engineering? Should I do Engineering?

An Expectancy-Value View of Student Engagement

Abstract

While ample empirical evidence supports the validity of the expectancy-value framework in understanding academic outcomes at all levels of education, much less is known about how and to what degree this framework manifests in engineering education. To understand these nuances, this paper uses a large dataset (n=1,837) collected from a survey at a single large public institution obtained from both in-person (prior to and following the COVID-19 pandemic) and remote (during the pandemic) learning settings in mechanical and electrical and computer engineering. Variables representing expectancy, value, and predictors of expectancy and value were integrated into hierarchical linear models to understand their influence on cognitive engagement and to explore whether or not the expectancy-value model was stable over time in the engineering education context. Consistent with expectancy-value theory, our results indicated that expectancy (measured by self-efficacy) and value (as measured by intrinsic and utility value) positively and significantly predicted cognitive engagement for all time periods. Previous academic achievements as measured by overall GPA was also consistent across all time periods in positively and significantly predicting self-efficacy. However, not all relationships were consistent. Incoming interest in studying engineering positively predicted self-efficacy across the different time periods, but did so only during remote learning settings for value. With regard to demographics, race, gender, U.S. status, and economic background also played a role in determining self-efficacy and value, but not all demographics were uniformly linked to self-efficacy and value across the different time periods studied. Thus, while this study adds additional empirical evidence to support the validity of expectancy-value theory, the dynamic nature of what influences expectancy (as measured by self-efficacy) and value over time also reinforces the importance of using multiple strategies to support students in believing that they can (self-efficacy) do engineering and should continue to pursue it as a valuable career choice.

Introduction

Engagement plays a significant role in determining the level of success that engineers can achieve, both during school and at work. In the workplace, employee engagement has been shown to increase productivity [1], retention rate [1], job satisfaction [2], and customer loyalty [3]. On a similar note, academic student engagement has been shown to be positively associated with critical thinking [4], academic achievement [5], retention in engineering degree programs [6], and persistence [7]. Retention in engineering is especially important as the demand for engineers continues to rise [8] while a significant number of engineering undergraduates still fail to complete their degree [9]. Since engagement can be measured on a short timescale (e.g., on a term-by-term basis), engagement measures provide an accessible antecedent to retention, persistence, and other academic and career outcomes that are limited to longer timescales.

In addition to engagement acting as a precursory investigable variable, the multifaceted definition of student engagement allows for flexibility in studying non-academic outcomes. Research indicates that delving into student engagement in the classroom may bring about intangible benefits in student identity, such as interpersonal development [10], [11] and an increased receptiveness to diversity and challenge [12]. These studies support the claim that engagement is a necessary component to a holistic and successful student experience in the classroom. It is also important to recognize how intrinsic interests coupled with student demographics can have a huge impact on the perceived student experience. The evolution of the relationship between self-efficacy, value, and their antecedents provides a timeline with which to analyze how to best foster engagement. To investigate this relationship, this study explores how students' expectancy and values influence their engagement in engineering classrooms before, during, and following the COVID-19 pandemic.

Background

While few researchers or educators would argue against the importance of engagement in education, considerable variability exists in the literature as to how to measure engagement and how to frame engagement in the larger picture of student well-being and success.

Measuring Engagement

Student engagement has been broadly studied in contexts ranging from elementary education to graduate school and from classrooms to different cocurricular and extracurricular activities. Unfortunately, engagement has also been defined in a wide variety of ways as well. When measuring engagement, a "tangled web of terms" [13] has emerged that has led to confusion in attempts to compare and contrast different articles, both in terms of research hypotheses as well as methodology. This lack of consensus can be traced back to the original works of Astin in involvement and Kuh in engagement. Astin's research of involvement primarily emphasized a combination of psychological energy expenditure and time on task [14]. Research in this domain includes the Cooperative Institutional Research Program (CIRP) [15] that was founded over 50 years ago to identify methods for improving student success; the primary activity of the CIRP is a survey administered to incoming freshmen targeted towards time on task on various collegiate activities. On the other hand, Kuh defines engagement using involvement theory which focuses on institutional factors and educational practices to establish more observable relationships among student behavior, institutional processes, and academic outcome [16]. Research using this definition can be seen in the National Survey of Student Engagement (NSSE), where engagement is measured using five benchmarks: "academic challenge, active and collaborative learning, student-faculty interaction, enriching educational experiences, and supportive campus environment." [13, p. 414].

The terms engagement and involvement are closely intertwined and often used interchangeably by some researchers [17], but the measures used in this study depart from both Astin's and Kuh's work by evaluating intentions rather than actions through the cognitive effort that students invest in their studies. This modified approach to academic engagement stems from motivational research [18], [19] and is defined as a multidimensional construct including behavioral, emotional, and cognitive components. Behavioral engagement primarily focuses on the actions taken by students via their participation in the classroom [19], while emotional engagement measures the response that students have following their classroom experience [20]. In this study, effort has been used to codify intent and aligns with the cognitive dimension of engagement to describe students' perception of their behavior in the classroom [18].

Evaluating COVID-19 Impacts
While it is widely recognized that student engagement dropped during the COVID-19 pandemic [21], [22], [23], much remains unknown about how engagement itself has changed with respect to the pandemic. While some studies state that post-pandemic, academic outcomes have begun to return to pre-pandemic levels [23], elements of engagement such as participation and attendance has not recovered to the same levels [21], [23]. For this reason, we study cognitive engagement (as measured by effort) before, during, and following the COVID-19 pandemic to better understand how the landscape of the engineering classroom has evolved over time. This approach can provide unique and timely insight for educators and administrators alike to positively influence cognitive engagement in the post-pandemic classroom.

Framing Engagement
The prominent educational psychologist Paul Pintrich stated: "Motivated students display interest in activities, feel self-efficacious, expend effort to succeed, persist at tasks, and typically use effective task and cognitive strategies" [9, p. V]. Understanding motivation is therefore key to understanding engagement and, in particular, to exploring the effort that students expend on their studies. To explore motivation and its association with engagement in multiple learning settings in engineering, this study draws on expectancy-value theory (EVT) as depicted in Figure 1. In the education context, expectancy-value theory posits that the degree to which a student expects to succeed in their chosen major *and* how much they value the education provided to them predict important academic outcomes such as, but not limited to, engagement [25].

Conceptual Framework

Expectancy-value theory provides a theoretical framework that can be used to inform policies and practices to improve academic achievement outcomes. The framework decomposes achievement outcomes into a combination of "students' expectancies for success and task values" [26, p. 617] as indicators of their motivation. Using this framework, educational policy makers have developed policies to improve student academic outcomes both in the classroom and on an individual scale [26], [27] through students' expectancies and values. This study leverages this framework to better understand how the COVID-19 disruption influenced the relationships among expectancy, value, and cognitive engagement (Figure 1).

Expectancy is often measured by self-efficacy and is defined as an individual's belief in their capacity to complete a task. Self-efficacy is representative of an individual's confidence in their competence with respect to a specific domain or area of activity and interest. Within the expectancy-value framework, self-efficacy has been shown to have positive associations with achievement outcomes such as persistence [28], [29], and academic achievement [30]. However, these associations are not always easily identifiable without additional variables, thereby necessitating an appropriate conceptual framework to provide additional context. Given its proven overlapping and conceptual similarity to expectancy, self-efficacy is used in this study to represent expectancy.

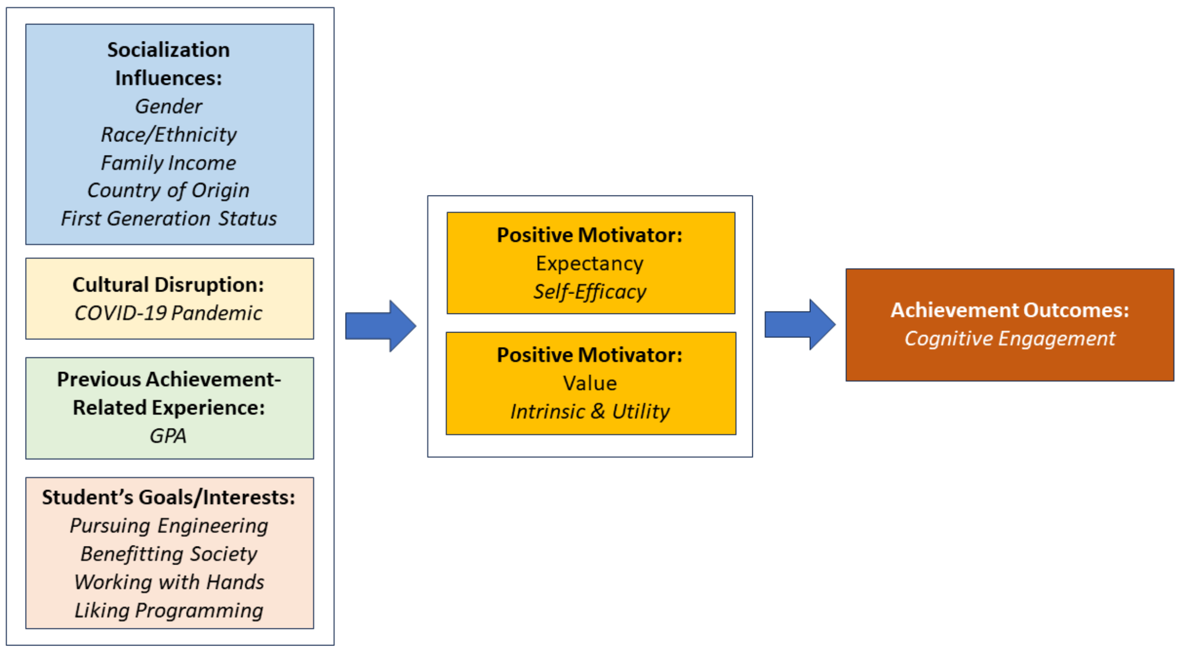

Figure 1: Expectancy-Value Framework Used in Study [31]

In the expectancy-value framework, ***value*** is not a single construct but is often represented by four different constructs: attainment, intrinsic, utility, and cost values [25], [32]. In education, *attainment* value refers to how important students' courses or other aspects of their education are to their identity. A student who identifies as an athlete will set attainment goals related to sports while a student who identifies as an engineer will ascribe value to skills, such as soldering or programming, which align with their chosen engineering discipline. While attainment value emerges from a student's internal identity, *intrinsic* value expresses students' internal enjoyment in the pursuit of goals or tasks. Students who pursue engineering because they enjoy building things, like programming, or are drawn to opportunities to serve society with their training, have higher levels of intrinsic interests than students pursuing engineering for the salary or status that engineering provides.

While attainment and intrinsic value tend to represent the internal values that motivate students, *utility* value represents the degree to which students perceive educational resources will fulfill their current or future career goals. For engineering students, an example of utility value is how doing well in a course could result in a high GPA or a letter of recommendation for jobs/internships and/or graduate school applications. On the other side of the spectrum, *cost* value represents the time and opportunity sacrificed in pursuit of a goal or completion of a task. A common theme for engineering is that courses are so rigorous that the cost of fully engaging in their engineering courses is high.

Consistent with existing literature that use multiple elements of value to investigate the nuances in academic outcomes [28], [29], [32], this study uses items that both reflect intrinsic and utility value. In addition to expectancy and value measures, several control variables are relevant to this study of cognitive engagement. Specifically, we control for gender, race, ethnicity, family income, first generation status, and international student status in our regression models. We also study the contribution of broad prior interests (to pursue engineering) as well as more specific intrinsic interests to self-efficacy, value, and ultimately to cognitive engagement.

Situating engagement in an expectancy-value framework provides our study with the opportunity to further validate expectancy-value theory via empirical evidence. It also allows us to study potential nuances in how both expectancy and value influence engagement in the specific context of engineering education. Understanding these relationships can support practitioners in advocating for engineering careers in ways that most effectively strengthen motivation to study, remain in, and work in engineering. More broadly, such understanding can also help to understand who is most at risk of leaving engineering and why.

Research Questions

The EVT framework applied to our mechanical, electrical, and computer engineering dataset led to the following research questions:

Research Question #1 (RQ1)
How well does the Expectancy-Value model predict Cognitive Engagement?
Demonstrating that both expectancy and value predict cognitive engagement in our dataset can provide further empirical support for the use of the expectancy-value model in engineering education. Validation of the expectancy-value framework in this study can also inform practitioners of the need to frequently reinforce the value of what is taught in engineering classes and build student self-efficacy (and expectancy) to support their academic success.

Research Question #2 (RQ2)
How do interests, demographics, and previous achievement influence expectancy or value?
It is not enough to demonstrate that expectancy and value predict cognitive engagement. Thus, answering this research question can inform actionable recommendations for teaching practices. Understanding demographic impacts on expectancy and value can also prevent a one-size-fits-all approach to teaching and facilitate enhanced support for underrepresented groups.

Research Question #3 (RQ3)
Did the COVID-19 pandemic impact the Expectancy-Value model for Cognitive Engagement?
Effective teaching in engineering education has been largely built upon the success and failures that come alongside traditional in-person teaching experience. However, the COVID-19 pandemic introduced a new variable that instructors were ill-equipped to handle – emergency remote teaching (ERT). Understanding how cognitive engagement evolved from pre-COVID to ERT to post-COVID within the expectancy-value framework can promote a new set of best practices for promoting cognitive engagement in the post-pandemic era.

Methods

Data from 1,837 unique (no duplicates) students was collected at a single public research institution in the United States was examined using hierarchical linear modeling (HLM). HLM is a type of ordinary least squares (OLS) regression that accounts for nesting while linearizing the relationship between one or more independent input variables and a single output variable. The mathematical foundations behind HLM can be found in [33]. In the case of the current study, the hierarchy/nesting explored was the variance in the study variables within different engineering courses. Null HLM models were used to identify whether the grouping variable (individual courses) had a significant impact on subsequent regression models. Variance due to nesting is measured through an intraclass correlation coefficient (ICC); for this study, greater than 0.05 or 5% variance due to nesting was used as the basis for using HLMs over ordinary regression models [34]. While multiple ICCs were under 5%, several ICCs were over 5% (Table 1), thereby confirming that nesting effects (within the different courses studied) were of potential concern and meriting HLM as a better choice for this analysis than ordinary linear regression methods. For consistency, data across all time periods (pre-COVID, ERT, post-COVID) and for all three dependent variables (expectancy, value, cognitive engagement) were analyzed using hierarchical linear modelling.

Table 1: Intraclass Correlation Coefficients for null HLMs

Model	Time Period		
	Pre-COVID	ERT	Post-COVID
Cognitive Engagement (measured as Effort)	0.002	0.05	0.05
Expectancy (measured as Self-Efficacy)	0.01	0.04	0.09
Value	0.1	0.2	0.1

Preliminary data analysis indicated that the models across all three time periods for cognitive engagement were similar; therefore, these models were combined into a single model. Separate models for pre-COVID, ERT, and post-COVID learning were retained for expectancy (measured as self-efficacy) and value due to significant variations in the relationships between the independent (e.g., demographics, interests) and dependent variables (expectancy and value) in the models for each time period.

Participant Demographics

Of the 1,837 respondents, most were male (n=1,361, 74.1%), Asian (n=801, 43.6%) or White (n=669, 36.4%). Many participants reported a family income between \$20,000 and \$100,000 USD per annum (n=879, 47.8%), and most students were continuing generation (n=1,397, 55.1%). Most student respondents were US citizens or permanent residents (n = 1,517, 82.0%) but nearly all the international students who reported their race were Asian (n = 282, 92.5%). Racial categories where representation was less than ten individuals in the entire dataset including Native American, Pacific Islander, and most mixed races were combined into a single category labeled "Other URM." A detailed breakdown of the student demographics is provided in Table 2. Non-responses reduced the final sample responses for each question, so the total number of respondents per question does not always add up to the total sample size. The reduced sample size for each question was still sufficiently large to continue forward with HLM.

Table 2: Demographics of study population (*n* = 1,837)

Demographic	Time Period							
	All		Pre-COVID		ERT		Post-COVID	
	n	%	*n*	%	*n*	%	*N*	%
Gender								
Male	1361	74.1%	522	75.5%	559	72.9%	280	73.9%
Female	499	24.4%	163	23.6%	198	25.8%	88	23.2%
Other	13	0.708%	3	0.434%	6	0.782%	4	1.06%
Race								
Asian	801	43.6%	275	39.8%	341	44.5%	185	48.8%
Black	45	2.45%	21	3.04%	16	2.09%	8	2.11%
Latino	72	3.92%	22	3.18%	30	3.91%	20	5.28%
White	669	36.4%	285	41.2%	273	35.6%	111	29.3%
Mixed Asian/White	18	4.41%	26	3.76%	40	5.22%	15	3.96%
Other URM	129	7.02%	51	7.38%	49	6.39%	29	7.65%
Family income (per annum)								
Low (< $20K)	126	6.86%	49	7.09%	54	7.04%	23	6.07%
Middle ($20K−$100K)	879	47.8%	356	51.5%	362	47.2%	161	42.5%
High (> $100K)	692	37.7%	237	34.3%	301	39.2%	154	40.6%
Family education								
First generation	387	21.1%	138	20.0%	167	21.8%	82	21.6%
Continuing generation	1397	55.1%	538	54.7%	580	56.8%	279	52.5%
U.S. Status*								
Domestic	1517	82.0%	571	82.2%	630	81.5%	316	82.8%
International	305	16.6%	117	16.9%	131	17.1%	57	15.0%

Percentages (of all respondents) may not add to 100% due to non-responses.
*U.S. Status "Domestic" includes U.S. citizens, permanent residents, and DACA recipients

Course Demographics

The forty-three courses surveyed in mechanical, electrical, and computer engineering are summarized in Table 3. Eight courses were surveyed pre-COVID, twenty-seven courses were surveyed in ERT during portions of 2020 and 2021, and eight were surveyed post-COVID.

Table 3: Courses Studied

Period of instruction (Engineering discipline)	*Participation*	
	N (% of responses)	Number of courses
Pre-COVID (Mechanical)	363 (19.8%)	3
Pre-COVID (Electrical and Computer)	328 (17.9%)	5
ERT (Mechanical)	205 (11.2%)	3
ERT (Electrical and Computer)	562 (30.6%)	24
Post-COVID (Mechanical)	80 (4.35%)	3
Post-COVID (Electrical and Computer)	299 (16.3%)	5
Total	1,837 (100%)	43

Procedures
IRB (Internal Review Board) approval was obtained to recruit and survey undergraduate students. Instructors were asked to offer the survey to their students within two to three weeks of the end of the term in which the course was offered. Instructors offered an incentive to students to complete the survey, with a nominal amount of extra credit being the most popular choice; extra credit has been shown to be a highly effective motivator for college students [35]. For all but one class in the pre-COVID and ERT time periods, the survey was hosted by an institution-specific survey tool (Catalyst WebQ) and students accessed and completed the survey via a link in the learning management system for the course (Canvas) within one to three weeks of the instructors publishing the survey. In the remaining course (a 2016 pre-COVID offering), students completed a paper version of the survey in class. In the post-COVID period, student responses were collected using either Catalyst WebQ (2022) or Google Forms (2023). Instructors were not provided with any survey responses but instead were provided with a list from the researchers of names and percentage of questions completed by each student so that grades could be adjusted according to the incentive offered to students. All participation was voluntary, and students were offered credit regardless of whether they granted consent for their responses to be used in the research because institutional IRB required that we not exclude those students who did not consent to the survey being used for research. Less than 5% did not offer consent and were eliminated from the dataset. Some students completed the survey more than once; in these cases, all but one response were randomly removed from the dataset, so that no duplicates remained in the final analysis.

Instruments
Likert scales were used for the measurement of self-efficacy (as a measure of expectancy), value, and cognitive engagement (Table 4). The *cognitive engagement* measure included two items adapted from previous studies [36] that reflect the mental effort that students are investing in courses rather than the specific behaviors (i.e., behavioral engagement) that reflect that effort [18]. The *self-efficacy* scale measured students' perception of their abilities within a specific domain (e.g., engineering). Although expectancy for success within the expectancy-value model that guided this study is defined as an individual's belief in their performance on tasks and is distinct from self-efficacy, the two constructs often overlap empirically and as a result, self-efficacy was used herein to measure expectancy [37]. Five items based on the previously validated Motivated Strategies for Learning Questionnaire (MSLQ) [38], [39] were used to measure self-efficacy. The *Value* scale contained six items that reflected both intrinsic and utility value extracted from previously validated positive emotional engagement scale [36] and a task value scale from the MSLQ [38], [39]. All measures were based on a 5-point Likert scale where responses ranged from strongly disagree to strongly agree.

Since all items were previously validated in pre-college rather than higher education setting and since items were drawn from multiple scales representing each variable, exploratory factor analyses were conducted on the dataset in previous analyses (not reported herein) to arrive at the final three scales used in this analysis. All three scales demonstrated a Cronbach's alpha of 0.80 or greater which is considered very good for internal consistency (i.e., how closely related the items were in each scale) [40]. Unfortunately, however, only two items remained from exploratory factor analysis to represent cognitive engagement; although a two-item scale is not ideal, its reliability (and internal consistency) can still be adequately measured using the Spearman-Brown coefficient [41]. The Spearman-Brown coefficient for the cognitive engagement scale was also greater than 0.8 which is considered sufficient to use the scale in the HLMs [41].

Table 4: Likert Scales used in This Study

Scale	*Items*
Cognitive Engagement ($\alpha = 0.81$; β = 0.82)	In this class, I work as hard as I can. In this class, I try hard to do well.
Self-Efficacy ($\alpha = 0.90$)	I'm confident I can understand the most complex material presented by the instructors in the classes in my major. I'm confident I can do an excellent job on the assignments and tests given in the classes in my major. I expect to do well in the classes in my major. I'm certain I can understand the most difficult material taught in the classes in my major. I believe I will receive excellent grades in the classes in my major.
Value ($\alpha = 0.87$)	I am very interested in the content of this class. I think the material learned in this class is useful for me to learn. It is important for me to learn the material presented in this class. I think I will be able to use what I learn in this class in my chosen profession. My quiz (or lab) section is fun. In this class, when we work on something, I feel interested.

(α = Cronbach's alpha measure of internal consistency)
(β = Spearman-Brown coefficient for predicted reliability)

In addition to these three scales, an additional ordinal variable was used to represent students' initial desire in pursuing engineering on a 5-point scale with 1 representing little interest ("Was completely undecided regarding my intended major") and 5 representing strong interest ("Intended to pursue my current major (or a closely related one) and never doubted the decision").

Data Coding

The four ordinal variables (self-efficacy, value, cognitive engagement, and the desire pursue engineering) were coded on a 5-point scale, with higher numbers on each scale reflecting larger amounts of the respective variable. Additional variables including demographics and additional intrinsic interests associated with engineering skills were effect coded.

Intrinsic interest is representative of the inherent enjoyment that students experience when performing a task or pursuing a goal. The intrinsic interests included in this study can be derived from [42] and include: "I like to program", "I find my major to have many opportunities to benefit society", and "I like to build things or work with my hands." Students were allowed to select more than one interest and all interests were effect coded as {did select that particular interest: +1, did not select that particular interest: -1}.

Effect coding was also used to code demographic variables and operates by applying weights to a categorical variable such that the weight of each category sums to 0. This was done in lieu of alternative methods such as dummy coding to remove potential racial, gender, or other bias from the regression models. For instance, the participants in this survey were asked to select their gender from “Male”, “Female”, and “Other.” For the variable labelled “Female”, the majority gender (male) was effect coded as -1; female as +1; and other as 0. In contrast to dummy coding which implies that the majority population is normal, effect coding simply compares across the grand mean of the study population [43] changing the way regression results and model interactions need to be interpreted [44]. A summary of all effect-coded demographic variables is provided in Table 5.

Table 5: Effect coded Demographic Variables used in this Study

Demographic	*Label*	*Effect Coding* -1	0	1
Race/Ethnicity*	Asian	White	Non-White, Non-Asian	Asian
	Black	White	Non-White, Non-Black	Black
	Latino	White	Non-Latino/a, Non-White	Latino
	Other URM	White	Asian, Black, Latino	Other
	Asian/White	White	Asian, Black, Latino, Other URM	Asian/White
Gender **	Female	Male	Non-Male, Non-Female	Female
Country of Origin	International	U.S.	NA	Non-U.S.
Annual Income (Family of Origin)	High	\$20k-\$100k	<\$20k	>\$100k
	Low	\$20k-\$100k	>\$100k	<\$20k
College Status***	First Generation	Continuing Generation	NA	First Generation

*Included only non-international students
**Non-binary genders not included in analysis due to very small sample size
*** First Generation: neither mother nor father completed four-year college degree

Data Analysis
Data analysis was conducted for this study using RStudio 2023.09.1. Hierarchical models were used to address the research questions. Three one-level HLM models were originally generated to explore RQ1 across the three time periods studied, but the models were sufficiently similar to combine the models into a single model. For the remaining models, preliminary analyses of the main effects indicated that pre-COVID, ERT, and post-COVID time periods were sufficiently different to necessitate individual models. The model used for RQ1 had only a single layer while the remaining two sets of models for self-efficacy and value had four layers which successively considered demographics (layer 1), GPA (layer 2), interests (layer 3) and potential interactions (layer 4). The first layer contained all student demographics (gender, race, U.S. status, family income, and first-generation status). The second layer added to the demographics layer and included previous achievements (GPA). The third layer added the strength of desire to pursue engineering as well as forms of intrinsic interest to the model. For self-efficacy and value models, interactions included all independent variables which the expectancy-value framework and changing significance values from layer to layer indicated could be of potential significance to the model. Back-wise stepwise regression was then used to eliminate interactions of non-significance (high p-value) until all Akaike’s information criterion (AIC) and Bayesian information criterion (BIC) values no longer decreased with the removal of interactions or only significant interactions remained.

Results

Descriptive statistics for all ordinal variables are summarized in Table 6. The excess kurtosis for all variables fell within the +/- 2 range that is considered acceptable for assuming a normal distribution [45]. The skew(ness) of all variables also fell within the acceptable range (+/-2) of a normal distribution [46, p. 66].

Table 6: Descriptive Statistics (Ordinal Variables)

Measure	*Mean*	*Median*	*Min*	*Max*	*SD*	*Skew*	*Kurtosis*[1]
Pursue Engineering							
Pre-COVID	4.08	4.00	1.00	5.00	0.954	-1.11	1.06
ERT	4.08	4.00	1.00	5.00	0.918	-1.17	1.48
Post-COVID	4.07	4.00	1.00	5.00	0.900	-1.12	1.45
GPA							
Pre-COVID	3.42	3.46	2.00	4.00	0.310	-0.905	1.80
ERT	3.49	3.51	1.90	4.00	0.313	-0.800	0.72
Post-COVID	3.49	3.50	2.37	4.00	0.313	-0.686	0.21
Self-Efficacy							
Pre-COVID	3.64	3.60	1.00	5.00	0.786	-0.353	0.06
ERT	3.57	3.60	1.00	5.00	0.795	-0.347	0.00
Post-COVID	3.78	3.80	1.20	5.00	0.830	-0.423	-0.07
Value							
Pre-COVID	3.93	4.00	1.00	5.00	0.796	-0.656	0.18
ERT	3.88	4.00	1.00	5.00	0.837	-0.826	0.78
Post-COVID	4.09	4.25	1.00	5.00	0.798	-0.898	0.74
Cognitive Engagement							
Pre-COVID	3.86	4.00	1.00	5.00	0.787	-0.391	-0.22
ERT	3.90	4.00	1.00	5.00	0.845	-0.570	0.08
Post-COVID	4.07	4.00	1.00	5.00	0.803	-0.751	0.50
[1]values given is excess kurtosis (kurtosis – 3)							

A one-way analysis of variance (ANOVA) of each ordinal variable demonstrated statistically significant differences across the three time periods studied (Pre-COVID, ERT, Post-COVID) for self-efficacy ($p < 0.01$), value ($p < 0.001$), and cognitive engagement ($p < 0.001$). These statistically significant differences are shown graphically in Figure 2.

Frequency data for students' intrinsic interests are summarized in Table 7. The most common intrinsic interest expressed by students was a desire to benefit society (67.4%) followed by an interest in working with the hands (60.2%) and enjoying programming (31.6%).

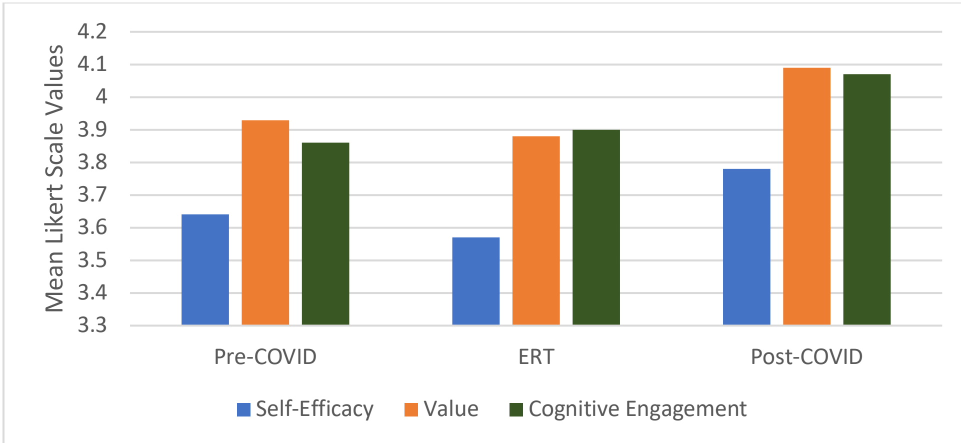

Figure 2: Likert Scale Values for Statistically Significant Ordinal Variables

Table 7: Intrinsic Interests

	N	%	*N*	%	*N*	%	N	%
Interest	All Students		Pre-COVID		ERT		Post-COVID	
Benefit Society	1239	67.4%	454	65.7%	527	68.7%	258	68.1%
Work with Hands	1106	60.2%	407	58.9%	465	60.6%	234	61.7%
Program	580	31.6%	151	21.9%	285	37.2%	144	38.0%

Column percentages add up to more than 100% because respondents could select “all that apply”

To ensure that multicollinearity did not affect the integrity of each HLM, variance inflation factors (VIFs) were calculated for each independent ordinal variable in all models. No variable exhibited a VIF exceeding 5, the threshold at which multicollinearity becomes a concern [47]. Once the usage of HLM was validated, three HLM models were constructed for each the ordinal variables: self-efficacy, value, and cognitive engagement, for a total of nine models to account for time in this study. Because the cognitive engagement models across the three time periods were similar, they were combined into one model. However, substantial differences were found in the model outputs for expectancy (as measured by self-efficacy) and value and warranted the use of three models each. Table 8 summarizes the HLM statistical measures for all models. No significant interactions between independent variables were found in the final seven models.

Table 8: Strength and Fit of HLMs

	Time Period		
	Pre-COVID	ERT	Post-COVID
Self-Efficacy			
Marginal R^2	0.137	0.142	0.141
BIC/AIC*	1,448 / 1,369	1,615 / 1,560	817 / 749
Value			
Marginal R^2	0.047	0.058	0.093
BIC/AIC*	1,437 / 1,357	1,640 / 1,559	802 / 734
Cognitive Engagement**			
Marginal R^2	0.279		
BIC/AIC*	3,885 / 3,857		

*BIC (Bayesian Information Criterion); AIC (Akaike Information Criterion)

HLM regression models for Self-Efficacy

Differences in the HLM model outputs dictated that the survey data be split into three time periods: pre-COVID, ERT, and post-COVID, as shown in Table 9. In the pre-COVID model, being female was significantly and negatively associated with self-efficacy (β = -0.15; $p <$ 0.001), whereas being Black American (β = 0.34; p = 0.026), GPA (β = 0.53; p < 0.001), desire to pursue engineering (β = 0.09; p = 0.002), and liking to program (β = 0.12; p = 0.001) were significantly and positively associated with self-efficacy. For the ERT setting, being female (β = -0.11; p = 0.002), being Black American (β = 0.55; p = 0.003), GPA (β = 0.60; p = <0.001), desire to pursue engineering (β = 0.10; p < 0.001), and liking to program (β = 0.07; p = 0.023) had similar trends to pre-COVID. Furthermore, other URM Americans (β = -0.49; p = 0.036) had a negative and significant association with self-efficacy while having a high family income (β = 0.12; p = 0.029) had a positive and significant association. During the post-COVID era, GPA (β = 0.66; p < 0.001) and the desire to pursue engineering (β = 0.11; p = 0.014) were still positively associated with self-efficacy, but being Asian American (β = -0.21; p = 0.038), having low family income (β = -0.35; p = 0.005), and having an interest in benefitting society (β = -0.11; p = 0.020) emerged as negatively associated with self-efficacy. No potential interactions were found to be significant and they were removed from the models.

Table 9: HLM Results for Self-Efficacy

Predictor Variable	Pre-COVID			ERT			Post-COVID		
	β (SE)	p		β (SE)	p		β (SE)	p	
Intercept	1.47 (0.34)	**<0.001**	***	1.09 (0.37)	**0.004**	**	1.07 (0.53)	**0.047**	*
				Demographics					
Female[1]	-0.15 (0.04)	**<0.001**	***	-0.11 (0.03)	**0.002**	**	-0.02 (0.05)	0.702	
Asian[1,2]	-0.10 (0.07)	0.167		-0.11 (0.08)	0.146		-0.21 (0.10)	**0.038**	*
Black[1,2]	0.34 (0.15)	**0.026**	*	0.55 (0.18)	**0.003**	**	-0.14 (0.29)	0.635	
Latino[1,2]	0.16 (0.15)	0.281		0.08 (0.14)	0.544		0.00 (0.18)	0.996	
Asian/White[1,2]	-.010 (0.13)	0.438		0.01 (0.12)	0.950		0.05 (0.20)	0.799	
Other URM[1,2]	-0.26 (0.15)	0.081		-0.49 (0.23)	**0.036**	*	0.32 (0.28)	0.268	
International[1]	-0.02 (0.05)	0.691		0.01 (0.05)	0.832		0.08 (0.07)	0.255	
First Generation[1]	-0.07 (0.04)	0.096		0.00 (0.04)	0.950		0.08 (0.06)	0.161	
High Income[1]	0.01 (0.06)	0.792		0.12 (0.05)	**0.029**	*	0.14 (0.08)	0.101	
Low Income[1]	0.04 (0.08)	0.634		-0.06 (0.08)	0.466		-0.35 (0.13)	**0.005**	**
				Previous Achievement					
GPA	0.53 (0.10)	**<0.001**	***	0.60 (0.10)	**<0.001**	***	0.66 (0.14)	**<0.001**	***
				Goals/Interests					
Pursue Engineering	0.09 (0.03)	**0.002**	**	0.10 (0.03)	**<0.001**	***	0.11 (0.04)	**0.014**	*
Benefit Society	0.00 (0.03)	0.918		0.03 (0.03)	0.326		-0.11 (0.05)	**0.020**	*
Work with Hands	-0.03 (0.03)	0.386		0.03 (0.03)	0.356		-0.01 (0.04)	0.900	
Like to Program	0.12 (0.04)	**0.001**	**	0.07 (0.03)	**0.023**	*	0.05 (0.04)	0.296	

**p<0.05; **p<0.01; ***p < 0.001*

HLM regression models for Value

Similar to the models for self-efficacy, the HLM models associated with value were split into three time periods because of differences in the model with respect to those time periods, as shown in Table 10. During pre-COVID, being Black American (β = 0.34; p = 0.026), enjoying working with the hands (β = 0.08; *p* = 0.012), and liking to program (β = 0.09; *p* = 0.016) were all positively and significantly associated with value. During ERT, enjoying working with the hands (β = 0.11; *p* < 0.001) had similar trends to pre-COVID. Additionally, the desire to pursue engineering (β = 0.09; *p* = 0.001) and having an interest to benefit society (β = 0.06; *p* = 0.048) were positively and significantly linked to value. During the post-COVID era, enjoying working with the hands (β = 0.12; *p* = 0.005) continued to have a positive and significant link to value. Post-COVID, having an interest to benefit society (β = -0.09; *p* = 0.048) became negatively and significantly associated with value while being an international student (β = 0.18; *p* = 0.007) and liking to program (β = 0.12; *p* = 0.007) had a positive and significant association with value.

Table 10: HLM Results for Value

Predictor Variable	Pre-COVID			ERT			Post-COVID		
	β (SE)	p		β (SE)	p		β (SE)	p	
Intercept	1.47 (0.34)	**<0.001**	***	1.09 (0.37)	**0.004**	**	1.07 (0.53)	**0.047**	*
Demographics									
Female[1]	-0.03 (0.03)	0.376		0.02 (0.03)	0.471		0.04 (0.05)	0.451	
Asian[1,2]	0.02 (0.07)	0.761		0.01 (0.08)	0.941		0.02 (0.10)	0.855	
Black[1,2]	0.34 (0.15)	**0.026**	*	0.29 (0.18)	0.103		-0.04 (0.29)	0.875	
Latino[1,2]	-0.13 (0.15)	0.361		0.07 (0.14)	0.619		-0.07 (0.17)	0.683	
Asian/White[1,2]	-0.17 (0.13)	0.199		0.04 (0.12)	0.742		-0.07 (0.19)	0.734	
Other URM[1,2]	0.00 (0.15)	0.989		-0.37 (0.23)	0.107		0.12 (0.28)	0.666	
International[1]	0.04 (0.05)	0.407		0.07 (0.05)	0.120		0.18 (0.07)	**0.007**	**
First Generation[1]	-0.03 (0.04)	0.472		0.05 (0.04)	0.163		0.09 (0.06)	0.131	
High Income[1]	-0.06 (0.06)	0.313		0.04 (0.05)	0.426		0.10 (0.08)	0.201	
Low Income[1]	0.08 (0.08)	0.315		-0.05 (0.08)	0.501		-0.23 (0.12)	0.060	
Previous Achievement									
GPA	0.05 (0.10)	0.606		0.11 (0.10)	0.295		-0.14 (0.14)	0.305	
Goals/Interests									
Pursue Engineering	0.04 (0.03)	0.166		0.09 (0.03)	**0.001**	**	0.06 (0.04)	0.178	
Benefit Society	0.04 (0.03)	0.210		0.06 (0.03)	**0.048**	*	-0.09 (0.05)	**0.048**	*
Work with Hands	0.08 (0.03)	**0.012**	*	0.11 (0.03)	**<0.001**	***	0.12 (0.04)	**0.005**	**
Program	0.09 (0.04)	**0.016**	*	-0.03 (0.03)	0.377		0.12 (0.04)	**0.007**	**

**p<0.05; **p<0.01; ***p < 0.001*

HLM regression models for Cognitive Engagement

Using self-efficacy and value as precursors for effort as shown in Figure 1, three models were generated to identify relationships for cognitive engagement. However, there were no significant differences from pre-COVID to ERT to post-COVID, resulting in the aggregation of these three models into a single model. Both self-efficacy (β = 0.48; *p* < 0.001) and value (β = 0.13; *p* < 0.001) were found to have positive and significant associations with effort (Table 11).

Table 11: HLM Results for Cognitive Engagement

	β (SE)	p	
Intercept	1.65 (0.10)	**<0.001**	***
	EVT Framework Variables		
Self-Efficacy (expectancy)	0.48 (0.02)	**<0.001**	***
Value	0.13 (0.02)	**<0.001**	***
	**p<0.05; **p<0.01; ***p < 0.001*		

Discussion

A single, one-level HLM was sufficient to explain how the measures of value and expectancy (as measured by self-efficacy) in this study predicted cognitive engagement among engineering undergraduates. However, in models where expectancy and value were dependent variables, the subsequent HLMs became far more nuanced and complex, thus necessitating three different models for both value and self-efficacy across the three time periods studied.

RQ1: How well does the Expectancy-Value Model predict Cognitive Engagement?
Our analysis provided further empirical evidence supporting the expectancy-value model [26] used as the conceptual framework in this study (Figure 1). Both value (measured as utility and intrinsic value) and expectancy (measured as self-efficacy) significantly and positively predicted cognitive engagement and did so consistently across all three time periods studied according to the HLM for cognitive engagement (Table 11). The strength of the regression model was also good as 27.9% of the variability in cognitive engagement was explained by value and expectancy.

RQ2: How do interests, demographics, and previous achievement influence expectancy or value?
Self-efficacy was used as a proxy for expectancy in this study. All three HLMs for self-efficacy Table 9) indicated a significant ($p < 0.001$) and positive association with GPA, with β (the slope of the regression line) ranging between 0.53 and 0.66. This association is consistent with Bandura's model of self-efficacy [48] which identifies mastery experiences (which would include previous GPA) as one of the four primary sources of self-efficacy.

While not as uniformly consistent as the GPA results, being Black was also significantly ($p < 0.05$) and positively associated with self-efficacy in two of the three HLMs used to explore self-efficacy. At first, this result appears to contradict previous studies that have demonstrated that Black students in general have lower self-efficacy than their peers in college [49], [50]. However, Reid [51] found that not all Black students have diminished self-efficacy. Instead, high achieving Black students tend to have higher self-efficacy than their majority peers. When considering that majoring in a STEM discipline has been significantly and positively correlated to high school GPA and SAT scores [52], higher self-efficacy among Black students in engineering is not surprising. However, these results also suggest that the impact of previous high achievement on the college experience may be greater for Black students than for other underrepresented minorities (URMs) as well as Asian and White students.

Unfortunately, it is also not surprising that being female was significantly ($p < 0.05$) and negatively linked to self-efficacy. This gender gap is consistent with previous studies that have shown female students to have significantly lower levels of self-efficacy than male students in engineering, physics, and mathematics courses [53]. Cech and her colleagues [54] suggested that these self-efficacy deficits emerge from both the subtle differences in the way males and females are treated in engineering as well as by mainstream views of what it means to be a good engineer.

In addition to racial and demographic differences in self-efficacy, the interests included in this study were also associated with greater self-efficacy. The stronger students' original commitment to their existing major, the higher their self-efficacy in that major. This suggests very simply that students are more interested in majors in which they see themselves as more able to succeed. However, this association did not extend to all specific interests associated with choosing engineering as a major and investigated in this study. Among the three interests (desiring to benefit society, wanting to build things/work with the hands, and liking programming), only one (liking programming) was significantly and positively correlated to self-efficacy and then, only in two of the three regression models for self-efficacy. Programming skill has been linked to higher levels of mathematics self-efficacy [55] and it is possible that this impacts self-efficacy in mathematics-intensive engineering courses, but the link between the interest itself (independent of programming skill that students are bringing to the table) could not be further explored in this study.

Value in this study used items that collectively represented both utility and intrinsic value. Unlike the self-efficacy regression models, student demographics did not have as consistent of an association to value across the three time periods. However, the three interests measured (desiring to benefit society, wanting to build things and work with the hands, and liking programming) were significant predictors of value in at six of the nine possible cases for the three regression models. Interest theory posits that one strategy to capture and raise student motivation in courses is through student interest [56]. Thus, our result is consistent with theory and previous studies [57], [58] that have demonstrated that interventions devoted towards promoting student interest develop intrinsic motivations, which in turns stimulates the perceived value of content.

RQ3: Did the COVID-19 pandemic impact the Expectancy-Value model for Cognitive Engagement?
To evaluate this research question, we looked at relationships between antecedents of both self-efficacy and value as defined by the EVT framework across multiple time periods (pre-COVID, ERT, and post-COVID).

Self-Efficacy: Numerous differences emerged across the different time periods in this study. Being female negatively predicted self-efficacy pre-COVID (β = -0.15; $p < 0.001$). This effect declined during ERT (β = -0.11; $p = 0.002$) and then again post-COVID (β = -0.02; $p = 0.702$) to the point that the effect was no longer statistically significant. Given that females experienced more stress, anxiety, and loneliness during the pandemic than males [59], this result is quite surprising. However, it is important to consider not only what was going on with female students during the pandemic but also to take a closer look at what was going on with male students. Research has indicated that male students benefit from face-to-face teaching compared to distance learning while females do not [60]. Thus, it is possible that the decline in the negative link between being female and self-efficacy from pre-COVID to ERT was a result of male students losing an advantage rather than female students gaining an advantage. The fact that being female in the post-COVID era is no longer negatively linked to self-efficacy also suggests that the hybrid offering of remote and in-person learning that has taken hold after ERT may also be contributing to levelling the playing field for females.

Looking at other underrepresented groups in our sample, being Black was significantly and positively associated with self-efficacy pre-COVID ($\beta = 0.34$; $p = 0.026$) and during ERT ($\beta = 0.55$; $p = 0.003$). However, this link did not persist in the post-COVID learning environment ($\beta = -0.14$; $p = 0.635$). Looking more closely at the data revealed that although the number of Black students as a percentage of the overall population during the three time periods studied remained about the same, the distribution of their self-efficacy did not. Pre-COVID, three of twenty-one Black students reported very low self-efficacy (i.e., a mean value of less than 3 on a 5-point Likert-scale), while post-COVID, three of eight Black students did so. This suggests that the dramatic decline in self-efficacy that Black students experienced from ERT to post-COVID (from a mean self-efficacy of 3.99 to a mean self-efficacy of 3.20) reflected a greater proportion of students who were struggling rather than a general decline. This may in part be due to the fact that Black student learning in general suffered more during the pandemic than other students and that catching up after COVID is a struggle for these students, or it may be due to a more complex set of factors. Regardless, the drop in self-efficacy for Black engineering students post-COVID is concerning and merits further study.

High income significantly and positively predicted self-efficacy during ERT ($\beta = 0.12$; $p = 0.029$), but not during pre- or post- COVID, suggesting that factors such as having better internet connections, equipment for online learning, and lack of family responsibilities may have had a role in the regression model results. This would be consistent with [61] showing how socioeconomic factors alongside resource limitations lowers self-efficacy, but students from high income backgrounds may not have these barriers to overcome. However, low income significantly and negatively predicted self-efficacy post-COVID ($\beta = -0.35$; $p = 0.005$), indicating that perhaps the effects of the COVID-19 pandemic may have disproportionally affected students with low family income, compounding into a lower self-efficacy once entering engineering. This trend is supported by research that demonstrates young adults had issues with adapting to remote learning [62] and that students from disadvantaged socioeconomic backgrounds suffered from a lack of access to resources (tutors, stable internet connections, spousal and family care, etc.) [63]. Further research needs to be done to explore the evolution of these relationships as students are further removed from the impacts of ERT.

In this study, students' GPA and their original commitment to pursue engineering were positively and significantly associated with self-efficacy across the three time periods surveyed, but such consistency was not evident within the three specific intrinsic interests studied. One noticeable trend is the decrease in positive and significant association between liking to program and self-efficacy from pre-COVID ($\beta = 0.12$; $p = 0.001$) to ERT ($\beta = 0.07$; $p = 0.023$) with the association lacking significance entirely post-COVID ($\beta = 0.05$; $p = 0.296$). However, this trend does not necessarily mean students interested in programming have less self-efficacy. When examining the responses that selected “liking programming”, the mean self-efficacy rose from pre-COVID to post-COVID. This hypothesis is further supported by the fact that although desiring to benefit society has a negative and significant association with self-efficacy (β = -0.11; p = 0.020), the mean-self efficacy also rose throughout time. Overall, we found that trends to vary from interest to interest and with respect to time period, implying that these interests are nurtured in and sensitive to the learning environment. How teaching practices are structured can heavily impact how these interests translate to self-efficacy and should be adjusted dynamically to support improved self-efficacy among engineering undergraduates.

Value: Intrinsic interests also differentially predicted value over time, most notably in the case of desiring to benefit society. While wanting to build things and work with hands was consistently positively and significantly linked to value, this was not the case for the other two interests. There was a positive and significant link between desiring to benefit society and value during ERT (β = 0.06; p = 0.048), but a negative and significant link post-COVID (β = -0.09; p = 0.048). This sudden shift suggests that there may have been a meaningful difference in teaching practices from ERT to post-COVID that affected how desiring to benefit society influenced student perceptions of the value of engineering. Also similar to self-efficacy, value increased from pre-COVID to post-COVID from a mean of 3.73 to a mean of 3.97. This upward trend in mean value bodes well for post-COVID teaching in engineering as students are viewing engineering as having more value and as a result, are likely to be more motivated to persist in engineering education and career pathways.

Limitations

All participants in this study were from a single, large public research institution in the U.S. and thus results may not be generalizable to other institutions. In addition, the racial composition of this population was skewed compared to overall U.S. undergraduate engineering enrollment [64]. Asian American students were substantially overrepresented (43.6%, vs. 14.7% nationally) and Black students were underrepresented (2.45%, vs. 4.4% nationally). In addition, only two engineering disciplines were measured, and both disciplines have historically had lower representation of women students relative to other engineering disciplines. Despite this potential bias, women were slightly overrepresented in this study (24.4% vs. 22.5% in engineering undergraduate programs nationally) [64]. Furthermore, while research regarding the underrepresented minority experience has shown that URM students face similar challenges with maintaining self-confidence, receiving adequate support for learning, feeling stigmatized, and finding a sense of belonging [65], [66]. URM groups also demonstrate distinct differences. Thus, results regarding the aggregate “Other URM” group in this study should be interpreted with caution.

Furthermore, the cross-sectional nature of this study inherently limits interpretation of the time component of the studied variables. Though multiple time periods were studied, each survey response is a single point in time and thus only associations can be confirmed. Future work should include exploring the direction of relationships exposed in this study. For instance, in the post-COVID world, self-efficacy is found to have a positive and significant association on cognitive engagement, but it would be beneficial to understand if students with low self-efficacy become less engaged with their courses, or if students who don't engage with their courses experience lower self-efficacy as a result.

Implications

The three different classroom time periods explored in this study: pre-COVID, ERT, and post-COVID demonstrate that the classroom settings are not constant. Evolution in engineering education will continue to persist in the future and require an examination into historical trends to determine the best learning strategies for instructors in order to devise their curriculum to maximize cognitive engagement. However, consistent with the EVT framework, both self-efficacy and value were positively and significantly associated with cognitive engagement regardless of classroom setting and time period. Thus, emphasizing the intrinsic interests of students, which act as predictor of both self-efficacy and value, may have a significant impact on the students' experience in their courses. The effectiveness of the classroom as a community should be nurtured by developing the interests of all students who are a part of that community, thereby improving their self-confidence in their abilities as an engineer and creating a more inclusive environment.

Conclusions

This study of engineering undergraduates in mechanical and electrical and computer engineering courses (n=1,837) has added further empirical evidence to the existing literature to support the validity of the expectancy-value model of motivation in the academic context. Results indicate that across multiple time periods (pre-, during-, and post- COVID-19 pandemic), value and expectancy (as measured by self-efficacy) positively and significantly predicted academic outcomes (as measured by cognitive engagement). This study also provided some additional insight regarding how value and expectancy vary with student interests and demographics. Results suggest that gender (being female), race (being Asian), and income (being from a low-income family background) may undermine the student experience in terms of lowered self-efficacy. In terms of value, this study also suggested that engineering highlights and nourishes some interests (e.g., programming, building things) while potentially devaluing or not sufficiently emphasizing other interests (e.g., desiring to benefit society). Future work will focus on exploring how and why these demographics and interests influence the student experience. Future work will also involve a longitudinal study to gain further insight into how to enable practitioners to influence expectancy and value for the benefit of student learning and other academic outcomes.

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