How Did the Landscape of Student Belonging Shift During COVID-19?

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Abstract

The goal of this study is to understand if and how emergency remote teaching (ERT) used during the COVID-19 pandemic changed the ways in which instructional support and interactions were linked to belonging among engineering students. Belonging is a fundamental human motivation associated with a wide range of positive psychological, educational, social, and job outcomes. Frequent and predominantly conflict-free interactions within a stable, relational framework of caring are required to facilitate belonging. To better understand potential shifts in belonging that occurred from pre-pandemic to mid-pandemic, this study used survey data from a cross-sectional dataset at a single, large institution comprised of sophomore to senior level students ($N = 1,485$) enrolled in engineering courses between 2016 and 2021. Hierarchical linear modeling (HLM) was used to study relationships among instructional support, instructor interactions, and belonging. The HLM models of ERT and traditional learning differed dramatically. In traditional classroom learning, race, interactions with faculty and teaching assistants (TAs), and instructional support were important factors in belonging. In ERT, certain motivations to study engineering (altruism; desire to build things) had nuanced associations with belonging, while race and interactions with faculty as well as with TAs became largely irrelevant. Most concerning, however, faculty interactions in traditional learning were negatively associated with belonging, indicating a need for a deeper understanding of the impact of those interactions. Further, the differences in the HLM models suggest that rather than returning to pre-pandemic traditional learning, a hybrid model that offers a more level playing field for marginalized students to find belonging in the classroom is recommended. In developing such models, faculty must take special care to avoid having a potentially negative impact on student belonging.

Introduction

When the World Health Organization declared COVID-19 a global pandemic on March 11, 2020, many higher education institutions in the United States chose to cancel face-to-face classes, laboratories, and other campus-based learning venues in favor of online delivery. This abrupt shift is different from traditional online education. In online education, course development time typically ranges from six to nine months and goes well beyond online content delivery to build learning communities that not only optimize instructional support but also provide strong social support to learners (Hodges et al., 2020). In contrast to courses designed from the start to be online, the COVID-19 crisis prompted a shift to emergency remote teaching (ERT) which, by its very nature, is a temporary delivery mode involving remote teaching that is intended to return to traditional face-to-face, blended, or hybrid mode once the crisis ebbs. The abrupt and unexpected shift to ERT during the COVID-19 crisis prompted many faculty to become "... instructional MacGyvers, having to improvise quick solutions in less-than-ideal circumstances." (Hodges et al. 2020, p. 2).

The rush to shift face-to-face instruction to online delivery emphasized the transfer of content rather than pedagogy. Not only did lectures and lecture sessions require shifting from the traditional classroom to video platforms, but these sessions also needed to be pre-recorded, recorded, or otherwise restructured to serve different time zones as students migrated back to homes around the world. Traditional in-classroom exams and other summative forms of assessment had to be redesigned at the same time that laboratories, design projects, and other co-curricular group activities needed to be overhauled to achieve existing internal and accreditation (ABET) outcomes. Understandably, this left little time to focus on developing the online social support structures that could ensure similar learning and psychological benefits to the formal and informal interactions that are taken for granted in campus-based college education. In online learning, the tones of instructor communication play a critical role in developing a trusting and caring environment for students. Successful navigation of social presence (i.e., open and meaningful communication between students and instructors and between students and peers) no longer happens organically as in a traditional classroom. Instead, it relies on strong, persistent, and qualified instructor presence to develop stable and meaningful bonds between instructor and student (Peacock & Cowan, 2019). Such bonds and the accompanying framework of caring that sustains them, in conjunction with frequent interactions with others, are critical antecedents to developing healthy belonging in any setting (Baumeister & Leary, 1995).

The lack of social support structures and other factors surrounding the abrupt transition to ERT prompted by COVID-19 was presumed to lead to sub-optimal teaching solutions that did little to build student belonging or offset the isolation of students trapped in dorm rooms or sequestered at home due to pandemic restrictions (Hodges et al., 2020). The research available regarding ERT has demonstrated that some impacts have indeed been negative. For example, in a one-semester study at a single institution, 97.2% of engineering students indicated that ERT had negative impacts on their belonging as a result of feeling disconnected from the university, finding it more difficult to develop relationships, and perceiving professors to be less approachable outside of class (Sheppard et al., 2022). A broader four-institution study of engineering and computer science students also reported negative impacts of COVID-19 and ERT (Casper et al., 2022) as 50% of students reported more stress in their lives during ERT and COVID-19, primarily due to the on-line format of classes as well as students' living situations and angst about the economy and the pandemic. But the percentage of students in this same study who felt equally included in courses by their instructors (compared to pre-pandemic) was over 50% at all schools involved in the study. More concerning, however, is that in the same four-institution study (Casper et al., 2022), the proportion of students who reported that they felt included by their classmates during ERT was lower, varying between 40% and 60% across schools. Fortunately, in online environments, peer support has been found to be of less value, often perceived to be superfluous, inconvenient, and not supportive of learning (LaPointe & Reisetter, 2008). Regardless, evidence to date has indicated that belonging in engineering education settings largely declined during ERT. Whether the manner in which belonging evolved in ERT was similar to or different than in the traditional setting, however, has yet to be explored and is the focus of this study. Knowing more about the landscape of belonging in ERT and traditional instructional settings will help us to gain greater insight into social support structures in engineering education. This study pursued such insight through the use of linear regression models to analyze belonging data collected both prior to the COVID-19 pandemic from 2016-2019 and during the COVID-19 pandemic from 2020-2021.

Background

Why Study Belonging?

Belonging (often also called sense of belonging or belongingness) embodies the feelings of security and stability that develop when an individual feels accepted, supported, and included in a group. The motivation to belong is considered fundamental to every human being, regardless of culture, status, race, ethnicity, gender, or other factors (Baumeister & Leary, 1995). When the need to belong is not fulfilled, an individual self-regulates less (Baumeister et al., 2005), is less capable of completing complex logic and reasoning tasks (Baumeister et al., 2002), and reports poorer mental health (Kitchen et al., 2012). Individuals who feel they do not belong also experience a wide range of negative emotions including but not limited to social anxiety, loneliness, jealousy, and social sadness (Leary, 2021) that can lead to debilitating psychological states such as depression (Hagerty & Williams, 1999), emotional exhaustion (Salles et al., 2019), suicidal ideation, and attempts at suicide (You et al., 2011). In contrast, when the need to belong is satisfied, individuals find life to be more meaningful (Lambert et al., 2013), are happier (Leung et al., 2013), are more motivated (Suhlmann et al., 2018), and exhibit greater well-being (Salles et al., 2019; Suhlmann et al., 2018) than those who do not belong. Thus, student belonging is a critical indicator of a healthy social support structure in the classroom.

How does belonging matter in college?

Research has demonstrated that college students who have strong belonging are more likely to graduate, perform better academically, have greater self-efficacy (students' perceptions of how well they can master skills in a particular domain), see higher task value in their courses of study, seek more help in their studies, and exhibit greater well-being than their peers with lower campus or classroom belonging. Studies that support these benefits are discussed next.

Belonging in college and persistence are tightly linked to one another, both conceptually and empirically. One of the most widely used models of student persistence is Tinto's model of Institutional Departure (1975). Recent modifications of Tinto's model (Tinto, 2017) focus on the student perspective for why students choose to leave or to stay in college. In this model, belonging as well as self-efficacy and student perceptions of the value offered by the curriculum influence student motivation. Student motivation, in turn, is critical to predicting persistence (Morrow & Ackermann, 2012). Ample empirical evidence also supports this central role of belonging in undergraduate persistence. For instance, a single-institution, longitudinal study of over 500 students showed that belonging within the university significantly and positively predicted actual persistence and intentions to persist for both White and African American students (Hausmann et al., 2007, 2009). Among Native American undergraduates at multiple universities, belonging at the university level also positively and significantly predicted intentions to persist, although belonging only explained 13% of the variance (Oxendine, 2015).

Studies that focus exclusively on STEM (science, technology, engineering, and mathematics) fields, have also affirmed the importance of belonging in predicting persistence. For instance, even after controlling for self-efficacy and exam performance, Lewis et al. (2017) determined that among almost 3,000 pSTEM (physical sciences, technology, engineering, and mathematics) students, belonging explained both intentions to persist and actual persistence and Marra et al. (2012) reported that a lack of belonging played a significant role in drop-out among engineering students. Similarly, in interviewing over 200 college seniors from STEM fields, Rainey et al. (2018) found that students who had persisted in STEM fields expressed a higher sense of belonging than those who had left. In another study of female engineering students (Verdin et al., 2018), belonging in the classroom was linked to intentions to persist in engineering for majority (White) women, although not for a sample of minority women (primarily Hispanic, 61%). Thus, while the importance of belonging overall is clear, research indicates that other factors may be at play which lead to more nuanced differences among some student groups.

Belonging is also strongly associated with improved academic performance outcomes. Undergraduate college achievement has been tied not only to college belonging (Han et al., 2017) but to having experienced prior belonging while in high school (Pittman & Richmond, 2007). In STEM, a national sample of first-year students majoring in the sciences revealed a significant and positive relationship between belonging and overall academic adjustment (Hurtado et al., 2007). Within engineering, social belonging (i.e., acceptance and membership) has been positively and significantly linked with grade performance in introductory engineering classes (Schar et al., 2017).

And for computer science students, lower (in-class) belonging, which includes elements of acceptance, membership, and support, has been linked to poorer academic outcomes, whether measured by course pass rate (Krause-Levy et al., 2021) or a specific post-course content assessment (Moudgalya et al., 2021).

Belonging in college has been linked not only to persistence and academic performance, but also to their many precursors. For example, a study of engineering students showed that social belonging was strongly associated with self-efficacy (Schar et al., 2017) and, more generally, first-year college students who felt belonging in their (non-major) classes exhibited higher intrinsic motivation, self-efficacy, and task value (Freeman et al., 2007). Greater motivation has, in turn, been linked to such positive academic outcomes as class participation and learning performance (Buzdar et al., 2017). And self-efficacy and task value have been associated with higher grades and greater persistence in technical fields (Lent et al., 1984) as well as with deeper approaches to learning (Khezri azar et al., 2010) and higher exam scores (Bong, 2001) in college. Other research has connected students' belonging with help-seeking strategies (McBeath et al., 2017; Won et al., 2021). Such strategies are self-regulatory and have enabled students to become more independent learners (Karabenick & Gonida, 2018) which in turn leads to greater academic success, either by directly impacting course grades (e.g., Karabenick, 2003) or by mediating the relationship between other student characteristics and academic outcomes (Holt, 2014). Students with strong belonging have also exhibited strong coping skills (Kember & Leung, 2004) and were generally more satisfied with college life (Thomas & Galambos, 2004). Among engineering undergraduates, a multi-institutional study linked belonging to multiple forms of engagement (Wilson et al., 2015). Engagement, in turn, has been shown to be a key contributor to academic performance in a meta-analysis of over 190,000 students (Lei et al., 2018). Furthermore, the outcomes of previous research on belonging in engineering education (Wilson et al., 2015) have been more frequently and more consistently linked to belonging at the class level than to belonging at the major or university level. For this reason, this study assessed belonging only at the class level.

How is belonging influenced in college? (the antecedents of belonging)

In college as well as in any other community setting, Baumeister and Leary (1995) hypothesized that fulfilling the need to belong requires two primary antecedents. The first antecedent requires that individuals have frequent positive or neutral interactions with other individual(s) who are members of the group with which they seek belonging and the second antecedent calls for these interactions to occur within a stable framework of caring that supports the development of reliable social bonds.

Frequent interactions with others: to fulfill belonging needs, all interactions with others in a group or community would ideally be positive and pleasant, but at a minimum, they should primarily be free from conflict and negative emotions (Baumeister & Leary, 1995). In a traditional, campus-based university setting, the learning environment naturally facilitates such interactions. Students have ample opportunity to interact with their peers in the classroom before and after class and during breaks, in study spaces, and in various common areas. In engineering and other applied majors, laboratory courses provide additional and often extensive opportunities for students to interact. Faculty, teaching assistants (TAs), and other instructors also have ample opportunity to interact with students before, during, and after class; in office hours, labs, and review sessions; and more informally, in the same campus spaces where students interact with each other. However, research has demonstrated mixed results when studying whether these interactions are positively linked to student belonging. For example, in a study of students at a single, commuter-based institution, Whitten et al. (2020) demonstrated that the frequency of interactions with faculty (as measured by how often they encouraged questions and participation) were significantly and positively correlated with student belonging. In contrast, in a study of 523 students from four different universities, Meeuwisse et al. (2010) demonstrated that informal interactions with faculty had no significant relationship to student belonging; however, for ethnic minority students (but not for majority students), better formal interactions with faculty regarding university and study-related matters led to greater belonging. This positive relationship between interactions with faculty and student belonging for under-represented groups has been reinforced in studies of overall interactions between faculty and international students (Glass et al., 2015) and for in-class interactions between faculty and Native American students (Strayhorn et al., 2016). Similar inconsistencies regarding the potential impact of interactions with faculty on student belonging have emerged from studies of TA interactions with students. For example, in a study of over 200 four-year institutions and over 26,000 students majoring in the sciences, the frequency of interactions with TAs was found to positively and significantly predict student belonging for underrepresented students but not for White and Asian students. Thus, the many opportunities for interaction between instructors and students in traditional classroom settings do not necessarily guarantee that these interactions will be sufficiently positive to improve student belonging. Further, in ERT settings where opportunities for interaction are drastically reduced compared to traditional classroom instruction, such guarantees may be even further out of reach.

Caring: for an individual to experience belonging in a group or community requires more than just interacting with members of that community. The individual must also feel that they are cared about and that the care is stable and ongoing (Allen et al., 2022). Research in higher education has supported this antecedent of belonging in college much more consistently than the relationship between frequency of interactions and belonging. For example, in studying students on a commuter-based campus, Whitten et al. (2020) found that whether or not students felt faculty instructors took an interest (cared about) in their development was one of three factors that had a significant and positive correlation to belonging. In another single institution study, Freeman et al. (2007) found significant positive links between an instructor's openness and warmth and student belonging at the class level. Conveying a sense of care can be especially important for fostering belonging among underrepresented students. For instance, in an interview-based qualitative study by Glass et al., (2015), faculty who conveyed a sense of care for students, particularly in one-on-one interactions, were credited with enabling a sense of belonging for international students. These studies underscore the importance of an atmosphere of care in the classroom. Compared to a traditional classroom, in online education, instructors must focus more attention on structuring course support to develop a strong and intentional environment of care (Peacock & Cowan, 2019). In an ERT setting, where a focus on relational and affective aspects of the classroom environment may take a backseat to content considerations, such caring bonds may not materialize, leading to reduced belonging and negative outcomes associated with unfulfilled needs to belong.

Conceptual Framework

In their seminal paper, Baumeister and Leary (1995) established a belonging hypothesis based on the premise that belonging is a fundamental human motivation preceded by frequent, positive (or at least neutral) interactions with others and a stable framework of care surrounding those interactions. This hypothesis is the foundation of the conceptual framework for our research (Figure 1). In this study, the frequency of two types of interactions (between faculty and students and between TAs and students) in traditional and ERT settings were studied. The second antecedent of belonging (caring) was measured using faculty, TA, and peer support scales that included items regarding how well students felt respected, supported, and cared for by faculty, TAs, and peers in their course experience.

Baumeister and Leary (1995) also posited that when an individual's need to belong is fulfilled, the individual will not necessarily seek further interactions or support. Such satiation of belonging needs could lead to fewer interactions with faculty or TAs among students who enter the classroom already feeling or predisposed to feeling as if they belong. Satiation is only one among several factors that can affect the link between the two antecedents of belonging and belonging for different groups of individuals. In this study, potential variability in these links was also explored in the context of gender, race, family income, first generation college status, citizenship, motivation, and self-efficacy.

Research Questions

To the best of our knowledge, this study is the first to explore how the landscape of belonging and its antecedents may have changed in ERT-based teaching during the COVID-19 crisis. The overall goal of our study was to explore such changes in the context of understanding how they can be leveraged to improve engineering instruction in the post-pandemic era. The following two research questions supported our goal:

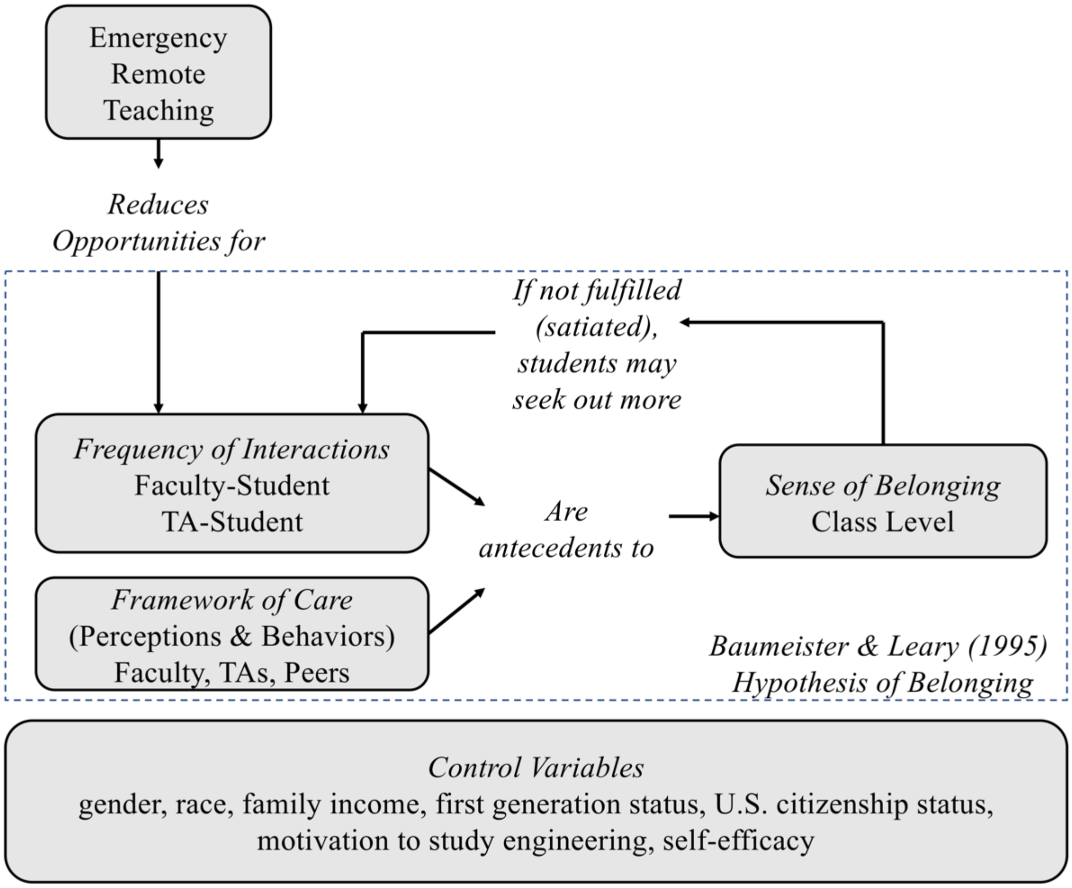

Figure 1: Conceptual Framework for this Research

Research Question #1 (RQ1)

In the traditional classroom, how are instructional support and interactions with instructors linked to belonging? As described earlier, existing research in higher education has shown that support and caring from faculty and TAs as well as interactions with these instructors are closely linked to the fulfillment of student belonging needs. Such support and interactions are likely to be domain specific due to differences in the educational experience across disciplines. Thus, studying belonging within a single domain (engineering) and in the classroom context offers the opportunity to more deeply understand what matters in students' belonging and in turn, to inform practitioner strategies to improve belonging.

Research Question #2 (RQ2)

In the ERT classroom, how are instructional support and interactions with instructors linked to belonging? While the peak of the COVID-19 pandemic has passed and ERT is becoming an instructional model of the past, many classrooms have not returned to the traditional, in-person setting that was the norm prior to the pandemic. Hybrid courses of all kinds have sprung up from ERT and understanding the landscape of belonging during ERT can inform how to best hybridize course offerings of the future to facilitate meeting the belonging needs of all students.

Methods

The landscape of belonging in the engineering classroom both pre-COVID and during COVID was examined using a hierarchical linear modelling (HLM) approach to analyze survey data collected from over 1,400 engineering students at a single institution in the U.S. HLM is a form of ordinary least squares (OLS) regression that analyzes the relationship between one or more independent, quantitative variables and a dependent output variable while accounting for hierarchy in the data. In this study, the hierarchy (i.e., nesting) in the data occurs through the variance that students share with a common instructor and classroom. HLM creates a simple regression model for every group (individual course) in the dataset and then uses the regression coefficients as outcomes in the next level of modelling to describe the variability across courses. To understand whether HLM is necessary to model the data or whether traditional OLS techniques are sufficient, a null HLM model is often used to evaluate whether the grouping variable (individual courses) significantly impacts the intercept (mean) of the dependent variable (belonging). Further detail regarding the mathematics involved in two-level models like the HLM approach used in this study can be found in a tutorial by Woltman et al. (2012).

For the data used in this study, null HLM models for pre-COVID (traditional classroom) and during COVID (ERT) data showed that course variation accounted for 1.2% and 9.1% of the variance in the null models respectively. The 9.1% shared variance (i.e., the nesting effect) was considered too large to ignore which merited the use of HLM to analyze RQ2. For the sake of consistency, HLM was also used to analyze RQ1. Belonging was used as the dependent variable in both models and the independent variables consisted of measures that represented the antecedents of belonging in our conceptual framework (Figure 1) as well as control variables like self-efficacy and demographics including race, gender, socioeconomic levels, and first-generation status. The dataset used to support analysis of RQ1 and RQ2 involved recruitment of student participants from over 29 courses which were offered between 2016 and 2021 in electrical and computer engineering and mechanical engineering at a large public institution in the US. The initial pre-COVID (traditional classroom) data were collected as part of an in-depth study of the contribution that belonging makes to various forms of engagement in the engineering classroom (Wilson, Summers, & Wright, 2020; Wilson 2020; Wilson, Wright, & Summers, 2020), but the survey scales also enabled investigation of the research questions in this study. During the COVID-19 crisis, the initial study duration was extended and ERT classrooms were integrated into the dataset in order to study RQ2.

Participant Demographics

Across traditional classrooms and ERT settings, a total of 1,485 students completed the survey associated with this study. Most students were male (N = 1,095, 73.7%) and either Asian (N = 634, 42.7%) or White (N = 579, 39.0%). Most student respondents were US citizens or permanent residents (N = 1,234, 83.1%) but nearly all the international students who reported their race were Asian (N = 223, 94.1%). Only 7.10% of participants (N = 106) came from families of origin whose household income was less than $20,000, while 21.2% ($N$ =315) reported as first-generation college students. A detailed breakdown of student demographics is provided in Table 1. Since some students did not respond to certain demographic questions, the total number of students in each demographic category does not always add up to the total sample size (N = 1,485). Non-responses also reduced the final sample size for the HLM models (from N = 721 to N = 664 in the traditional setting and from N = 764 to N = 697 in the ERT setting). However, the reduced population sizes were still sufficiently large to proceed with HLM.

Table 1. Demographics of study population (N = 1,485)

Demographic Variable	*N*	%	*N*	%	*N*	%
Gender	All Students		Traditional Setting		ERT Setting	
Male	1,099	74.0%	544	75.5%	555	72.6%
Female	371	25.0%	172	23.9%	199	26.0%
Other	8	0.50%	3	0.42%	5	0.65%
Race	All Students		Traditional Setting		ERT Setting	
Asian	634	42.7%	295	40.9%	339	44.4%
Black	42	2.83%	26	3.61%	16	2.09%
Other URM	200	13.5%	91	12.6%	109	16.4%
White	579	39.0%	297	41.2%	282	36.9%
Family income	All Students		Traditional Setting		ERT Setting	
Low (< $20K)	106	7.10%	56	7.77%	50	6.54%
Middle ($20K−$100K)	735	49.5%	371	51.5%	364	47.6%
High (> $100K)	548	36.9%	245	34.0%	303	39.7%
Family education	All Students		Traditional Setting		ERT Setting	
First generation	315	21.2%	148	20.5%	167	21.9%
Continuing generation	1132	76.2%	559	77.5%	573	75.0%
U.S. Status	All Students		Traditional Setting		ERT Setting	
Domestic	1229	82.8%	592	82.1%	637	83.4%
International	247	16.6%	127	17.6%	120	15.7%

Percentages (of all respondents) may not add to 100% due to non-responses.
Other URM = Other underrepresented minority students (not Asian, Black, or White)

Course Demographics

The 29 courses surveyed in mechanical and electrical and computer engineering are summarized in Table 2. Twenty-two courses, including 52% of all participants, were surveyed during ERT in 2020 and 2021; seven courses, including 48% of all participants, were surveyed during traditional classroom learning between 2016 and 2018. The student response rate ranged from 7% to 93% across all 29 classes, but the overall response rate was 69% of all enrolled students in the courses studied.

Table 2. Courses Studied

Mode of instruction (Engineering discipline)	*Participation*		*Student response rate*			
	N (% of participants)	Number of courses	Overall, this class type	Min	Median	Max
Traditional (Mechanical	378 (25%)	3	78%	29%	83%	93%
Traditional (Electrical)	343 (23%)	4	72%	42%	78%	85%
ERT (Mechanical)	203 (14%)	3	55%	7%	58%	78%
ERT (Electrical)	561 (38%)	19	70%	16%	71%	88%
Total	1,485 (100%)	29	69%			

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 (Foltz et al., 2021). For all but one class, 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 offering), students completed a paper version of the survey in class. Since most of the surveys in the traditional setting were collected online, no drastic changes needed to be made to the data collection procedures during ERT. Therefore, we considered it reasonable to extend the study into the ERT period of instruction. 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 2% did not offer consent and were eliminated from the dataset. Some students were present in more than one class and duplicate records increased the probability of bias in the estimates and standard errors in the regression models (Sarracino & Mikucka, 2017). Thus, duplicates were identified and one among each duplicate, triplet, etc. was randomly retained for analysis. The final dataset contained no duplicates and was entirely cross-sectional.

Instruments

Likert scales for the dependent variable used in this study (belonging) as well as many of the independent variables (faculty, TA, and peer support; faculty and TA interactions, self-efficacy) were validated in previous studies. The remaining variables used in the HLM models were demographics and were pre-processed according to coding methods described in the next section (Data Coding).

Belonging (dependent variable): When applied to academic settings, scales designed to measure belonging have not been consistently operationalized (Table 3). Some have drawn upon the work of Goodenow (1993) to measure students' belonging to the school as a whole, with a strong focus on feelings of acceptance. Other studies have drawn more heavily on the work of Walton and Cohen (2007), to instead emphasize a student's feelings of membership, self-identity, and self-efficacy. Still other belonging scales have focused on commitment, acceptance, engagement, and connectedness (Anderson-Butcher & Conroy, 2002; Wilson et al., 2015). Nearly all the belonging scales applied to engineering education have included elements of acceptance, whether at the level of an individual class, a department, or more generally within an academic domain (Wilson & VanAntwerp, 2021). A number of these scales include an item that directly uses the word "belong" (e.g., Banchefsky et al., 2019; Good et al., 2012; Smith et al., 2013). However, the fact that there are so many scales and items intended to assess this concept is a good indication that the understanding of the meaning of the word "belong" may be inconsistent. Thus, in this study, we chose to avoid the direct use of "belong" and used four items (Table 3) that included elements of acceptance, membership, and support in a local context (i.e., the classroom).

Table 3: Examples of Belonging Scales for Academic Settings

Context	*Items*	*Focus*	*Sample Item(s)* [1]	*References*
Class (college)	4	Acceptance Membership Support	I feel that I am supported in this class. I feel that I am a part of this class. I feel that I am accepted in this class. I feel comfortable in this class.	This study; Wilson et al., 2015
School (K-12)	28	Acceptance Respect	People here notice when I'm good at something Other students in this school take my opinions seriously	Goodenow, 1993

School (K-12)	17	Acceptance Membership	I feel like an outsider at [school name]. I think in the same way as do people who do well at [school name].	Walton & Cohen, 2007
Class (college)	2	Acceptance Membership	Peers accept my ideas or interpretations I feel like a member of this class	Hogue, 2012
Major (college)	6	Acceptance Membership Identity	I feel like I belong in STEM People in STEM are a lot like me	Banchefsky et al., 2019
Disciplin e (college)	28	Acceptance Membership	When I am in a math setting… I feel respected I feel like I belong	Good et al., 2012
Class (college)	4	Acceptance Membership	I feel comfortable in this class I feel part of this class I feel supported in this class	Kissinger et al., 2009
Class (college)	4	Membership	I can relate to the people around me in my class I have a lot in common with the other students	Marra et al., 2012

These four items are consistent with Baumeister and Leary's hypothesis of belonging (1995) as well as the conceptual framework used in this study and have been previously validated in studies of youth development programs (Anderson-Butcher & Conroy, 2002) and higher education (Wilson et al., 2015). In this study, the four-item belonging scale demonstrated a reliability (Cronbach's alpha) of 0.83 and a one factor confirmatory factor analysis indicated none of the items had factor loadings less than 0.68. Thus, all items were retained in the belonging scale for subsequent analyses.

Instructional Support (three independent variables): The survey that was used to measure belonging in this study also asked students to report their perceptions of various items related to instructional support from faculty, TAs, and peers. Instructional support was used as a measure of the framework of care (Figure 1) that individuals involved in the classroom experience provide to students. For faculty support (eleven items) and TA support (twelve items), this meant not only student perceptions of care (respect, interest, interest) but also behaviors that expressed such care (e.g., organizing the class, being available for students, asking questions). Peer support was measured only in terms of perceptions of care (e.g., friendly, helpful, supportive, reliable). This approach was consistent with the multiple facets of peer support developed by Thompson and Mazer (2009). All support scales used items that were validated in previous studies using a five-point Likert scale ranging from 1 - Strongly Disagree to 5 - Strongly Agree.

Instructor Interactions (two independent variables): Whereas instructional support was used to measure the framework of care as an antecedent to belonging, the frequency of interactions between students and instructors was used to measure the second primary antecedent to belonging in our conceptual framework (Figure 1). Items for both interaction scales were validated in previous studies and were measured on a 5-point scale ranging from 1-Never to 5-Very Often. The faculty interactions scale included eight items that included both in person (during office hours) and online (over email) interactions which emphasized exchanges regarding academic performance and work, career, course selection, broader intellectual discussions, and socializing. Although previous tool development efforts included a similarly broad range of items covering interactions with TAs, factor analyses in those studies (Wilson, Wright, & Summers, 2020) reduced TA interactions to only four items which were focused on discussions of academic performance, intellectual discussions, course selection, and career plans. Despite the reduced number of items, the reliability of the TA interactions scale (α = 0.92) was the same as that for faculty interactions for the dataset used in this study.

Self-efficacy: Academic self-efficacy emerges from a students' perceptions of how well they can master skills in a particular domain. A large body of research has demonstrated the importance of domain-specific or academic self-efficacy in predicting academic performance (e.g. Honicke & Broadbent, 2016), motivation (e.g., Lin et al., 2022), adjustment to college (e.g., Chemers et al., 2001), and other academic and affective outcomes. A small subset of these studies has demonstrated the importance of self-efficacy in predicting belonging (e.g., Freeman et al., 2007) and belonging uncertainty (e.g., Höhne & Zander, 2019). Thus, it was important to control for self-efficacy in the HLM models used in this study. Based on the previously validated Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich & DeGroot, 1990; Pintrich et al., 1993), the self-efficacy scale used in this study contained five items and included judgments about one's ability to accomplish a task as well as confidence in one's skills to perform that task.

Self-efficacy and the other five scales used for independent variables in this study all demonstrated reliabilities (Cronbach's alpha) greater than 0.70. Sample items from each of these six scales are provided in Table 4 along with references to studies where the scales were previously validated as well as the reliabilities of the scales associated with this study. In confirmatory factor analyses for both traditional and ERT settings, at least three items in each of the six scales had factor loadings greater than 0.7 and demonstrated goodness of fit as measured by the root mean square error of approximation (RMSEA) of 0.055 and 0.057 for traditional and ERT settings respectively. Values of RMSEA between 0.05 and 0.08 are considered acceptable in factor analyses (Fabrigar et al., 1999). Thus, all items in the six scales were retained for the HLM regression analyses.

Table 4: Independent ordinal scales used in this study
(α =Cronbach's Alpha measure of internal consistency)

Scale	*Previously Used/Validated*	*Sample Item(s)*
Faculty Support ($\alpha = 0.92$)	Van Ryzin et al., 2009; Wilson, Summers, & Wright, 2020	The professor (primary instructor) has clearly explained course goals and requirements. The professor (primary instructor) in this class cares about how much I learn.
TA Support ($\alpha = 0.92$)	Wilson, Wright, & Summers, 2020	At least one of the TAs (or secondary instructors) in this class is available when I need help. At least one of the TAs (or secondary instructors) in this class treats me with respect.
Peer Support ($\alpha = 0.87$)	Van Ryzin et al., 2009	In this class, other students are helpful to me. In this class, other students are a reliable resource to me.
Faculty Interactions ($\alpha = 0.92$)	Wilson, Summers, & Wright, 2020	I have attended office hours to see the professor (primary instructor) in this class.
TA Interactions ($\alpha = 0.92$)	Wilson, Wright, & Summers, 2020	I have discussed my academic performance with at least one of the TAs or secondary instructors in this class.
Self-efficacy ($\alpha = 0.89$)	Pintrich & DeGroot, 1990	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.

Data Coding

Likert Scale Variables: In lieu of standardization or centering, the six sets of items used to calculate the six scales (Table 4) that represented the independent variables in this study as well as the items used to calculate the belonging scale (Table 3) were summed and divided by the total number of items in each scale in order to obtain values with a minimum possible value of 1 and a maximum possible value of 5. The remaining independent variables in the HLM models were computed from demographic items using effect coding.

Demographic Variables: Effect coding assigns different weights to the levels of a categorical variable such that the weights sum to zero. For example, two variables could be used to effect code gender. The first could assign a value of -1 to males, 0 to non-binary individuals, and +1 to females and the second coded variable could assign a value of -1 to males, 0 to females, and +1 to non-binary individuals. In the alternative, dummy coding approach, the first coded variable would assign a value of +1 to females and value of 0 to males and the second coded variable would assign a value of +1 to non-binary individuals and 0 to males. In a regression model that dummy codes gender in this way, the results would inherently reference the regression results to males (e.g., "Being female is associated with lower belonging than being male") while effect coding would inherently reference the regression results to the grand mean (i.e., the unweighted mean) of all effect coded groups (e.g., "Being female is associated with lower belonging than the grand mean/norm in the study population"). Effect coding changes the way both main effects and interaction effects are interpreted in regression models (UCLA, 2021). While dummy coding implies that what the majority population is doing is normal, effect coding avoids this bias altogether by not assigning "normal" to any particular group but instead making comparisons to the grand mean across all study participants (Mayhew & Simonoff, 2015). Thus, to minimize bias in this study, effect coding was used to transform all demographic variables (including motivation levels) to -1, +1 or -1, 0, +1 values for inclusion in the HLM regression models. A summary of effect coded demographic variables is provided in Table 5.

Table 5: Effect coded variables used in this study

Category	*Label*	*Effect Coding*		
		-1	0	1
Race*	Asian	White	non-White or non-Asian	Asian
	Black	White	non-Black or non-White	Black
	Other URM	White	Black	non-Black or non-White
Gender	Female	Male		Female
International	International	U.S. citizen or permanent resident		not a U.S. citizen or permanent resident
Income**	High	\$20k-\$100k	<\$20k	>\$100k
	Low	\$20k-\$100k	>\$100k	<\$20k
College Status	First Generation	mother or father completed 4-year degree		neither mother or father completed 4-year degree
Motivation	Relative Math & Science Build Things Altruism Programming	student did not indicate this motivation		student did indicate this motivation

* Included only U.S. Citizens or permanent residents because a large majority of international students reported their race as Asian and evidence that international students in engineering report a different experience than Asian American students (e.g., Bai et al., 2021)

** Annual income associated with family of origin

Some groups were not effect coded due to small sample sizes (e.g., only 8 students or 0.50% of respondents reported as non-binary) and some were combined into a single group (e.g., Other URM included all participants who were not Black, Asian, or White) to increase overall sample size for that group. An exception was made for Black students who, although small in number (*N* = 42), demonstrated significant differences in their responses from other URM students in preliminary data analyses; thus, Black students were retained as a group separate from Other URM in the data coding process.

Motivation: To include elements of what motivated students to study engineering in the HLM models associated with this study, students were also asked to report what motivated their choice to study engineering. Students were presented with a list of motivations derived from previous studies of engineering students (Wilson et al., 2009-2015) and were free to choose any one or more of the following:

- My father, mother, or close relative has worked in the field of my chosen major ("Relative")
- I did well in math and/or science in high school ("Math and Science")
- I find my major to have many opportunities to benefit society ("Altruism")
- I like to build things or work with my hands ("Build Things")
- I like to program ("Programming")

Motivations were also effect coded as detailed in Table 5.

Data Analysis

All data analyses were performed using software RStudio, Version 1.3.1056 (RStudio, 2020). A two-level hierarchical linear model (HLM) was used to address RQ1 and RQ2 with the first level of modelling representing the independent variables and demographic variables associated with this study and the second level accounting for the effects of course-to-course variation (i.e., nesting effects). In preliminary analyses, both ERT and traditional instruction were included in a single series of models to address both RQ1 and RQ2. However, a detailed look at the significant main effects and interaction effects in these preliminary analyses showed that the traditional and ERT learning were sufficiently different that a different set of models was merited for each setting.

Thus, five HLM models were used to explore each of RQ1 and RQ2 with each model including the variables from the previous model as well as additional variables. All models included student demographics (gender, race, U.S./international status, family income, and first-generation status). Model 2 added motivations to study engineering and self-efficacy. From Model 2, Model 3 added faculty and TA interactions and Model 4 then added faculty, TA, and peer support. In each series of models, the last model (Model 5) added interaction effects to the variables included in Model 4 by initially including interactions between independent variables whose significance shifted from one model to the next (either becoming significant or losing significance). Interactions were then removed from Model 5 using a backward stepwise regression approach until all remaining interactions were significant or the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) no longer decreased with further reductions in the model.

Results

Descriptive statistics for all ordinal variables (both dependent and independent) are summarized in Table 6. Independent samples t-tests did not identify any significant differences between traditional and ERT settings. While Likert-scale data are better suited for non-parametric Mann Whitney tests, a recent study indicated that the results for parametric t-tests and the non-parametric Mann Whitney counterpart produce almost equal type 1 errors and demonstrate very small differences in statistical power between the two tests (De Winter & Dodou, 2010). Thus, independent samples t-tests were considered sufficient for this study.

Table 6: Descriptive Statistics (Ordinal Variables)

Measure	*Mean*	*Median*	*Min*	*Max*	*SD*	*Skew*	*Kurtosis*
Self-Efficacy							
Traditional	3.63	3.60	1.00	5.00	0.78	-0.41	0.18
ERT	3.60	3.60	1.00	5.00	0.81	-0.38	0.04
Faculty Interactions							
Traditional	1.73	1.38	1.00	5.00	0.90	1.72	2.64
ERT	1.74	1.38	1.00	5.00	0.88	1.69	2.68
TA Interactions							
Traditional	1.49	1.00	1.00	5.00	0.88	2.26	4.73
ERT	1.49	1.00	1.00	5.00	0.89	2.16	4.26
Faculty Support							
Traditional	3.96	4.00	1.18	5.00	0.64	-0.56	0.47
ERT	3.95	4.00	1.00	5.00	0.7	-0.71	0.60
TA Support							
Traditional	3.61	3.67	1.08	5.00	0.77	-0.46	0.00
ERT	3.68	3.75	1.00	5.00	0.76	-0.41	-0.10
Peer Support							
Traditional	3.83	4.00	1.00	5.00	0.77	-0.42	-0.26
ERT	3.81	4.00	1.00	5.00	0.85	-0.60	0.08
Belonging							
Traditional	3.81	3.75	1.00	5.00	0.7	-0.41	0.32
ERT	3.79	3.75	1.00	5.00	0.78	-0.56	0.49

The kurtosis (i.e., the peakedness of the data distribution) of all variables fell within the acceptable range of a normal distribution between -7 and +7 for all variables (Byrne, 2010; Hair et al., 2010). For all but one variable, skewness fell within the rule-of-thumb range between -2 and +2 (Byrne, 2010; Hair et al., 2010) for normal distributions. The skew of TA interactions was only slightly more positive than +2 and reflects the fact that a majority of students in both ERT and traditional settings never had the types of interactions with TAs indicated by the items on the TA interactions scale regardless of whether they felt they did or did not belong.

Students also reported what motivated them to study engineering (Table 8). The most common reasons to study engineering were doing well in math and science in high school (70%), finding engineering would have many opportunities to benefit society (68%), and enjoying working with the hands and building things (59%).

Table 8: Motivations to Study Engineering

	Students	
*Motivation to Study Engineering**	*N*	*%*
My mother or father or close *relative* has worked in the field of my chosen major	364	24
I did well in *math and science* in high school	1035	70
I find my major to have many opportunities to benefit society (*altruism*)	1007	68
I like to *build things* or work with my hands	871	59
I like to *program*	442	30

* text in italics represents label used to identify this motivation in HLM results

Before proceeding with creating the two HLM models to examine the research questions in this study, key assumptions of HLM were verified. Like other forms of linear regression, HLM assumes that little to no multicollinearity occurs in the data and that independent variables within the model are not highly correlated with one another. Multicollinearity contributes to overfitting of the model and errors in the regression results. To check for multicollinearity, variance inflation factors (VIF) were calculated for all independent ordinal variables in each set of models. None of the independent, ordinal variables indicated a VIF greater than five where conservatively, multicollinearity becomes problematic (James et al., 2013).

Linear regression also assumes that there is a linear relationship between the independent variables and the dependent variable (belonging). No non-random effects were visually detected in the model residuals that would suggest the data were non-linear. Finally, a variation of Levene's test (Palmeri, n.d.) was performed to verify assumptions of homoscedasticity (i.e., homogeneity of variance) to ensure that the error term between each independent variable and the dependent variable was similar across all of the independent variables. Levene's test did not reject the null hypothesis ($p > 0.05$), thus indicating that homogeneity of variance was not violated.

Once all assumptions of HLM were satisfied, a series of five HLM models for each research question was constructed. Table 9 presents the random effects and model fit characteristics for each model. Both the BIC and AIC criteria decreased in successive models through and including Model 4. Once interactions were added in Model 5, BIC increased slightly but AIC decreased again, indicating that overall, the quality of the models increased as more variables were added to the model. The R^2 coefficients of determination indicated that once all the variables were added to the model, 68% and 78% of the variance in belonging was accounted for in traditional (RQ1) and ERT (RQ2) models respectively.

Table 9: Random Effects and Model Fit for Models associated with RQ1 and RQ2

Refer to Tables 9 and 10 for Fixed Effects associated with each Model

	Model Number				
	1	2	3	4	5
Research Question #1 (Traditional Setting)					
Random Effects					
Within Course Variance (σ^2)	0.47	0.35	0.35	0.16	0.16
Between Course Variance (τ^2)	0.01	0.01	0.00	0.00	0.00
Intra-Class Correlation Coefficient (ICC)	0.01	0.02	0.01	0.01	0.01
Model Fit					
Marginal R^2	0.026	0.269	0.282	0.664	0.682
Conditional R^2	0.040	0.281	0.291	0.668	0.683
Bayesian Information Criterion (BIC)	1464	1311	1313	828	834
Akaike Information Criterion (AIC)	1414	1235	1227	729	708
Research Question #2 (ERT Setting)					
Random Effects					
Within Course Variance (σ^2)	0.56	0.43	0.41	0.14	0.13
Between Course Variance (τ^2)	0.05	0.03	0.02	0.01	0.01
Intra-Class Correlation Coefficient (ICC)	0.08	0.06	0.06	0.04	0.04
Model Fit					
Marginal R^2	0.011	0.248	0.273	0.767	0.774
Conditional R^2	0.086	0.293	0.313	0.777	0.783
Bayesian Information Criterion (BIC)	1680	1526	1504	762	781
Akaike Information Criterion (AIC)	1630	1448	1417	662	654

Based on the model fit characteristics in Table 9, both HLM models were retained for further analysis. Model results that describe the relationship between demographics and other independent variables and belonging during traditional learning (pre-COVID) are summarized in Table 10.

Table 10. Multilevel Model Results for Belonging during Traditional Learning

	Model 1		Model 2		Model 3		Model 4		Model 5	
	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*	β (SE)	*p*
Intercept	3.76 (0.12)	**<0.001**	2.03 (0.16)	**<0.001**	1.89 (0.16)	**<0.001**	-0.39 (0.14)	**0.006**	-0.73 (0.24)	**0.002**
Gender										
Female	-0.03 (0.03)	0.275	0.02 (0.03)	0.425	0.03 (0.03)	0.328	-0.02 (0.02)	0.300	-0.01 (0.02)	0.507
Race, being American and										
Asian	-0.11 (0.06)	**0.053**	-0.02 (0.05)	0.693	-0.01 (0.05)	0.775	-0.04 (0.03)	0.263	-0.22 (0.10)	**0.049**

Black	0.30 (0.01)	**0.010**	0.13 (0.10)	0.189	0.10 (0.01)	0.311	0.08 (0.07)	0.245	0.23 (0.13)	0.766
Other URM	-0.20 (0.07)	**0.004**	-0.13 (0.06)	**0.033**	-0.12 (0.06)	**0.049**	-0.07 (0.04)	0.088	-0.06 (0.04)	0.168
Other Demographics										
International	0.01 (0.04)	0.839	-0.00 (0.03)	0.909	-0.01 (0.04)	0.745	0.00 (0.02)	0.915	0.01 (0.02)	0.642
High Income	0.06 (0.11)	0.551	0.13 (0.09)	0.171	0.15 (0.09)	0.118	0.12 (0.06)	0.059	0.12 (0.06)	**0.036**
Low Income	0.01 (0.06)	0.911	0.03 (0.05)	0.616	0.03 (0.05)	0.511	-0.02 (0.04)	0.664	-0.01 (0.03)	0.808
First Generation	-0.05 (0.03)	0.186	-0.04 (0.03)	0.206	-0.04 (0.03)	0.186	-0.02 (0.02)	0.182	-0.02 (0.02)	0.244
Student Motivation										
Relative			-0.02 (0.03)	0.384	-0.03 (0.03)	0.353	-0.02 (0.02)	0.378	-0.02 (0.02)	0.403
Math and Science			-0.01 (0.03)	0.741	0.00 (0.03)	0.901	0.00 (0.02)	0.900	0.02 (0.02)	0.876
Build Things			0.02 (0.02)	0.357	0.02 (0.03)	0.389	-0.01 (0.02)	0.670	-0.02 (0.02)	0.207
Altruism			0.03 (0.03)	0.274	0.03 (0.03)	0.259	-0.00 (0.02)	0.809	0.03 (0.02)	0.276
Programming			-0.01 (0.03)	0.637	-0.02 (0.03)	0.601	-0.03 (0.02)	0.183	-0.03 (0.02)	0.151
Self-Efficacy			0.45 (0.31)	**<0.001**	0.43 (0.03)	**<0.001**	0.14 (0.02)	**<0.001**	0.16 (0.02)	**<0.001**
Frequency of Interactions with Instructors										
Faculty					0.09 (0.05)	0.058	-0.05 (0.03)	0.174	-0.40 (0.10)	**<0.001**
TAs					0.00 (0.05)	0.999	0.05 (0.04)	0.135	0.61 (0.12)	**<0.001**
Level of Support										
Faculty							0.55 (0.03)	**<0.001**	0.74 (0.05)	**<0.001**
TAs							0.13 (0.03)	**<0.001**	0.14 (0.03)	**<0.001**
Peers							0.24 (0.02)	**<0.001**	0.08 (0.05)	0.091
Black American* Altruism									0.09 (0.05)	0.073
Black American * Build Things									-0.05 (0.03)	0.067
Asian American * Altruism									-0.06 (0.03)	0.084
Asian American * Self-Efficacy									0.06 (0.03)	**0.048**
Faculty Support * TA Interactions									0.09 (0.02)	**<0.001**

Peer Support * Faculty Interactions	-0.14 (0.03)	**<0.001**

p values in bold indicate a significant association ($p < 0.05$)

In the final model (Model 5) of traditional learning (RQ1, Table 10), being Asian American was significantly associated with lower belonging compared to the RQ1 population as a whole (β = -0.22; p =.049) as were interactions with faculty (β = -0.40; $p < 0.001$). Coming from a family of origin with a high household income positively and significant predicted belonging (β = 0.12; $p = 0.036$). Since income and race were effect coded, these results are stated relative to the grand mean of belonging rather than to the level of belonging expressed by the majority group (e.g., White Americans for category race). Significant results for the remaining ordinal independent variables indicated that self-efficacy significantly also positively predicted belonging (β = 0.16; $p < 0.001$) as did TA interactions (β = 0.61; $p < 0.001$), faculty support (β = 0.74; $p < 0.001$), and TA support (β = 0.14; $p < 0.001$). Interaction effects between Asian Americans and self-efficacy were also significant ($p < 0.001$) (Figure 2) as were interaction effects between faculty support and TA interactions ($p < 0.001$) (Figure 3) and between peer support and faculty interactions ($p < 0.001$) show in Figure 4. In each of Figures 2, 3, and 4, the gray bands around each regression line represent the 95% confidence interval for that line.

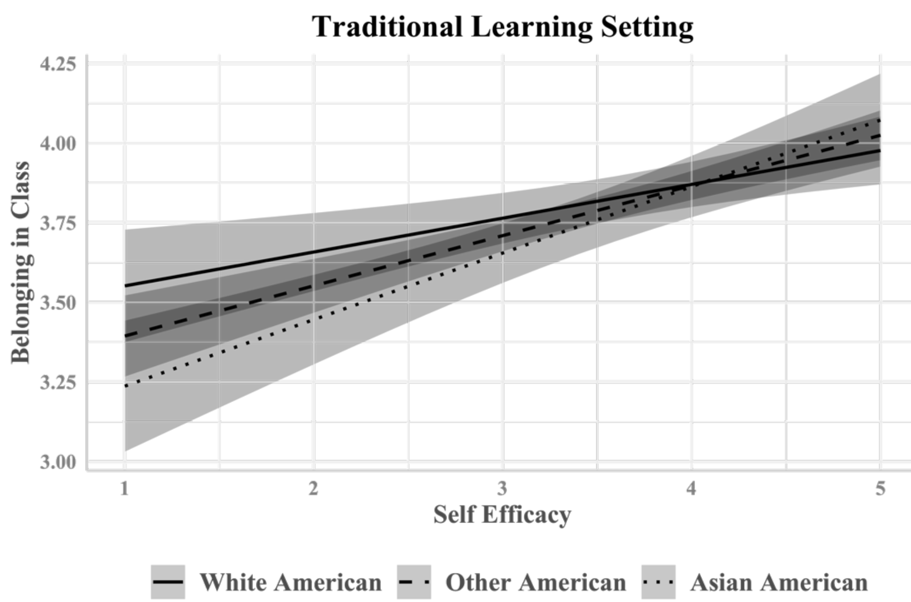

Figure 2: Interaction Effects between Race and Self-Efficacy

Visualization of these interaction effects suggest that at lower levels of self-efficacy, Asian American students not only reported a lower sense of belonging, but the increase in belonging they reported with increased self-efficacy was larger than for the population as a whole.

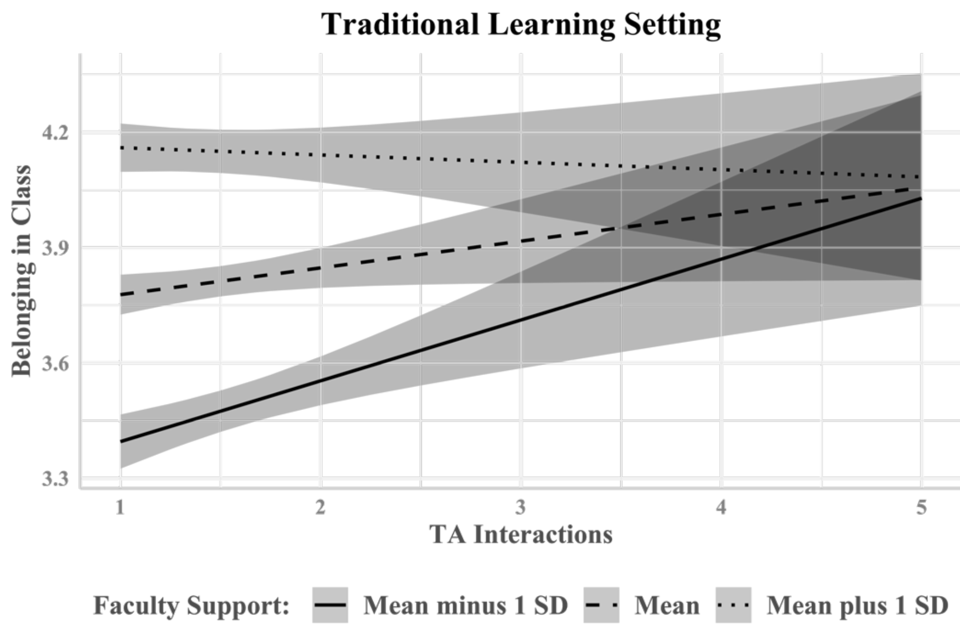

Figure 3: Interaction effects between Faculty Support and TA Interactions

Visualization of these interaction effects suggest that the more faculty support students receive, the less TA interactions are linked to belonging.

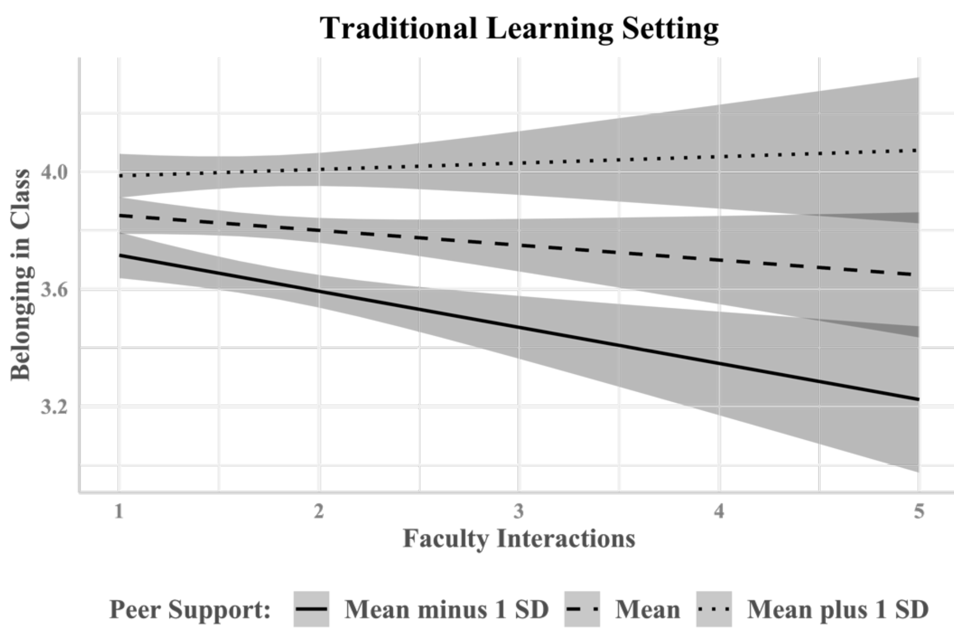

Figure 4: Interactions between Peer Support and Faculty Interactions

Visualization of the interaction data suggests that the more peer support students receive, the less faculty interactions are linked to belonging.

A separate series of HLM models was used to examine the ERT setting. The models were structured similar to those for the traditional learning setting and are summarized in Table 11.

Table 11. Multilevel Model Results for Belonging during ERT

	Model 1 β (SE)	p	Model 2 β (SE)	p	Model 3 β (SE)	p	Model 4 β (SE)	p	Model 5 β (SE)	p
Intercept	4.04 (0.14)	**<0.001**	2.26 (0.17)	**<0.001**	2.07 (0.18)	**<0.001**	-0.76 (0.13)	**<0.001**	-1.06 (0.21)	**<0.001**
Gender										
Female	-0.03 (0.03)	0.378	0.02 (0.03)	0.584	0.01 (0.03)	0.804	-0.02 (0.02)	0.346	-0.02 (0.02)	0.239
Race, being American and										
Asian	-0.05 (0.07)	0.484	-0.00 (0.06)	958	0.00 (0.06)	0.929	-0.02 (0.04)	0.651	-0.02 (0.03)	0.672
Black	0.18 (0.16)	0.259	0.10 (0.14)	0.462	0.09 (0.14)	0.528	0.03 (0.08)	0.701	0.04 (0.08)	0.606
Other URM	-0.02 (0.08)	0.792	0.01 (0.07)	0.887	0.02 (0.07)	0.822	0.02 (0.04)	0.631	0.01 (0.04)	0.760
Other Demographics										
International	-0.01 (0.05)	0.811	0.01 (0.04)	0.890	-0.02 (0.04)	0.616	0.02 (0.02)	0.387	0.01 (0.02)	0.611
High Income	-0.06 (0.12)	0.615	0.00 (0.11)	0.969	0.04 (0.11)	0.685	0.08 (0.06)	0.221	0.06 (0.06)	0.331
Low Income	-0.12 (0.06)	0.064	-0.05 (0.06)	0.380	-0.07 (0.06)	0.210	-0.03 (0.03)	0.284	-0.02 (0.03)	0.544
First Generation	0.05 (0.04)	0.178	0.04 (0.03)	0.236	0.05 (0.03)	0.133	-0.01 (0.02)	0.698	-0.01 (0.02)	0.438
Student Motivation										
Relative			-0.01 (0.03)	0.722	-0.01 (0.03)	0.796	-0.03 (0.02)	0.144	-0.03 (0.02)	0.077
Math & Science			0.03 (0.03)	0.315	0.03 (0.03)	0.298	0.02 (0.02)	0.246	0.02 (0.02)	0.166
Build Things			0.02 (0.03)	0.566	0.02 (0.03)	0.429	0.04 (0.02)	**0.009**	-0.10 (0.10)	0.337
Altruism			0.07 (0.03)	0.013	0.07 (0.03)	**0.018**	0.03 (0.02)	*0.076*	0.27 (0.09)	**0.003**
Programming			0.00 (0.03)	0.980	0.00 (0.03)	0.897	-0.04 (0.02)	**0.006**	-0.04 (0.02)	**0.005**
Self-Efficacy			0.45 (0.03)	**<0.001**	0.42 (0.03)	**<0.001**	0.17 (0.02)	**<0.001**	0.17 (0.02)	**<0.001**
Frequency of Interactions with Instructors										
Faculty					0.22 (0.05)	**<0.001**	0.01 (0.03)	0.780	0.01 (0.03)	0.757
TAs					-0.10 (0.05)	0.027	-0.02 (0.03)	0.383	0.11 (0.11)	0.286
Level of Support										
Faculty							0.62 (0.03)	<0.001	0.66 (0.05)	**<0.001**
TAs							0.18 (0.03)	<0.001	0.22 (0.03)	**<0.001**
Peers							0.21 (0.02)	<0.001	0.20 (0.02)	**<0.001**
Low Income * Build Things									-0.05 (0.03)	0.080

Faculty Support * Altruism	-0.06 (0.02)	**0.006**
Faculty Support * Build Things	0.07 (0.03)	**0.015**
Faculty Support * TA Interactions	-0.03 (0.02)	0.173
TA Support * Build Things	-0.06 (0.03)	**0.016**
Peer Support * Build Things	0.03 (0.02)	0.102

p values in bold indicate a significant association ($p < 0.05$)

Unlike in traditional learning, no demographic characteristics were significantly associated with belonging in any of the five models. However, significant main effects emerged for two types of motivation to study engineering. Altruism (i.e., pursuing engineering for opportunities to benefit society) significantly and positively predicted belonging (β = 0.27; $p = 0.003$); and affinity for programming significantly and negatively predicted belonging (β = -0.04; $p = 0.005$). Further, unlike the traditional model (Table 10), neither the frequency of faculty interactions nor frequency of TA interactions were associated with belonging, but peer support (β = 0.20; $p < 0.001$) emerged alongside faculty support (β = 0.66; $p < 0.001$) and TA support (β = 0.22; $p < 0.001$) as significant and positive main effects. Three interaction effects were significant in the ERT series of HLM models. Two of these significant interactions were related to motivations to study engineering based on desiring to build things. The interaction between students motivated by building things and faculty support was significant ($p = 0.015$) (Figure 5) meaning that belonging among students motivated in this way increased more dramatically with increasing faculty support than was the norm among students in ERT.

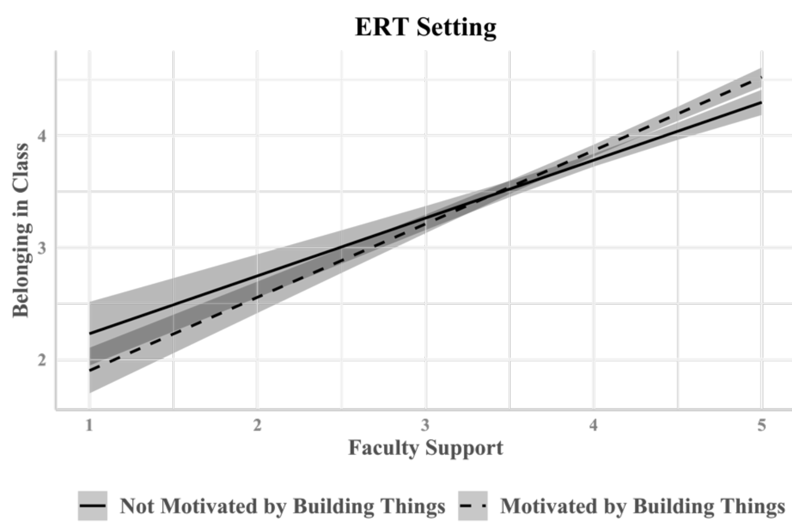

Figure 5: Interaction Effects between Faculty Support and Desiring to Build Things
Visualization of the interaction effects suggests that increases in belonging with increasing faculty support are larger for students who are motivated by building things vs. those who are not so motivated.

The opposite was true for TA support (p = 0.016) where belonging among students motivated by a desire to build things increased less steeply with increasing TA support than was the norm among students in ERT (Figure 6). Interaction effects between faculty support and altruistic motivations were also negative and significant (p = 0.006) (Figure 7). In each of Figures 5, 6, and 7, the gray bands around each regression line represent the 95% confidence interval for that line.

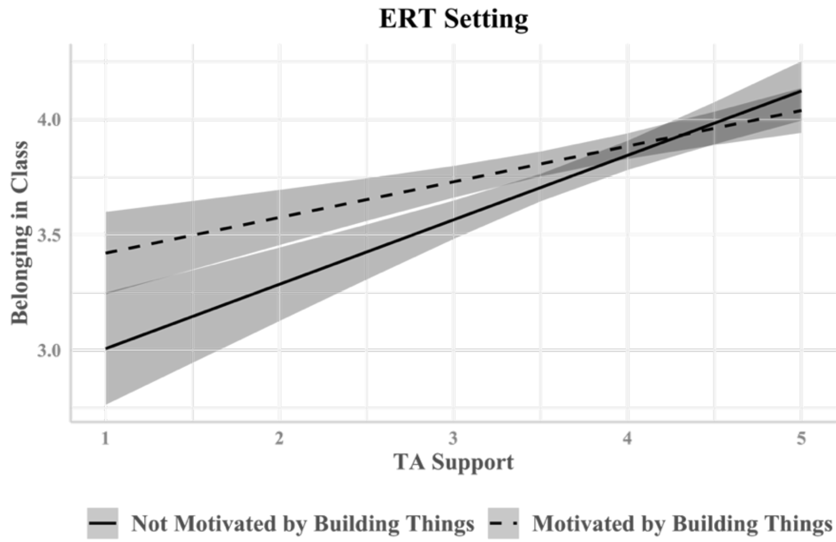

Figure 6: Interaction Effects between TA Support and Desiring to Build Things
Visualization of the interaction effects suggests that increases in belonging with increasing TA support are smaller for students who are motivated by building things vs. those who are not motivated by such a desire.

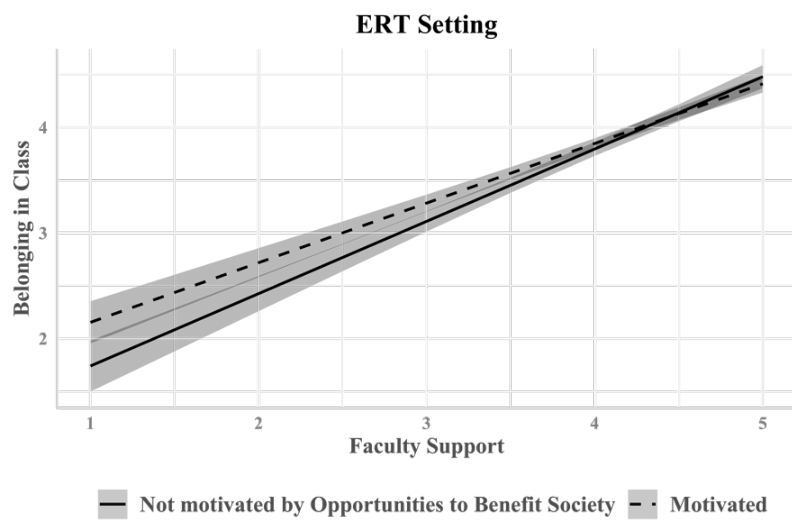

Figure 7: Interaction Effects between Faculty Support and Desiring to Benefit Society
Visualization of the interaction effects suggests that not only are students who are motivated by a desire to benefit society (i.e., altruism) more inclined to experience belonging in class at a given level of faculty support but also increases in belonging with increasing faculty support for those students are smaller for these students than for other students.

Discussion

This study was focused on understanding how belonging was linked to engineering students' perceived support and care from faculty, TAs, and peers as well as interactions with instructors (faculty, TAs) in a traditional and ERT-based teaching environment. The study was guided by a conceptual framework (Figure 1) based on Baumeister and Leary's hypothesis of belonging (Baumeister & Leary, 1995) that treats instructor interactions and the framework of care (support) they provide to students as antecedents to students' belonging. The framework also controls for race, gender, first generation and immigration status and motivation, which may color how students perceive instructor support and interactions, thus impacting their belonging.

Belonging, Support, and Interactions in a Traditional Learning Environment

HLM results in the traditional setting were well aligned with the conceptual framework (Figure 1), in that most support and interactions were positively associated with students' belonging. By far, faculty support demonstrated the strongest association while TA support indicated a weaker association. This reinforces the conceptual framework and prior work, which position the sense of care and support instructors (faculty and TA) provide in the classroom as being an important antecedent to students' sense of belonging. Frequent interactions with TAs also positively and significantly predicted belonging. This result is unsurprising as it is supported by previous research which has shown that TAs are viewed more as peers than as "professors" (Muzaka, 2009) and therefore are more likely than faculty to convey psychological benefits to students.

Not all of our results were positive. In fact, faculty interactions were negatively associated with belonging. While concerning, this result is not unexpected as prior research has shown mixed results when studying whether faculty interactions were linked to student belonging (Glass et al. 2015; Meeuwisse et al., 2010; Strayhorn et al., 2016; Whitten et al, 2020). Nevertheless, the negative link in this study suggests that adverse interactions may be occurring between faculty and students. This possibility is especially concerning because a majority of students (over 75%) reported having interacted with faculty in the traditional learning environment (Table 7). Although this study is cross-sectional and does not prove causality, the possibilities for the interpretation of the results are nevertheless worrisome. For example, if faculty interactions are directly decreasing students' sense of belonging, then that is cause for concern. Conversely, if students with low sense of belonging are increasingly interacting with faculty and yet maintaining their low sense of belonging, that too is alarming. Therefore, regardless of the causal relationship, this result raises a red flag, but a longitudinal study would be required to more fully understand how interactions with faculty are detrimental to students' belonging. At the very least, these results support implementing professional development programs that can help faculty to better navigate the nuances associated with student interactions and ensure that these interactions remain primarily positive and supportive.

Belonging, Support and Interactions in a ERT Learning Environment

Students' belonging has been widely studied in an in-person, traditional classroom setting. In this study, we have expanded our understanding of student belonging by investigating the relationship between belonging and its antecedents in an ERT setting. We found that students' belonging was not significantly different in ERT than in traditional learning, but unlike the traditional environment, interactions with faculty and TAs were no longer associated with belonging. This contrasts with our conceptual framework (Figure 1) and reinforces the notion that ERT was not ideal for supporting instructional interactions, a finding that is consistent with prior research (Colclasure et al., 2021; Shim & Lee, 2020).

The fact that interactions with others were not associated with belonging casts further doubt on the sustainability of ERT. While the role of instructional care and support in linking to belonging seemed to have successfully transitioned into ERT, the positive psychological impacts that comes from interactions with others did not seem to carry over. Such positive impacts were likely limited by "Zoom fatigue" or burnout caused by extensive use of videoconferencing technology to deliver classes during ERT. Such fatigue has proven negative psychological impacts including reduced motivation and emotional exhaustion (Bullock et al., 2022), resulting in an unhealthy teaching and learning environment. Our findings from ERT also provide insights on what a way forward in engineering education might look like because faculty interactions were no longer negatively linked to belonging as they were in a traditional learning environment. Prior evidence has shown (Gebreegziabher 2021; Nadworny 2019) that in office hours and other spaces where students interacted with faculty online during ERT, students felt both safer (because they were in a familiar space like home) and less intimidated than they would be when physically walking into the unfamiliar space that is the professor's office. As students return to a traditional, in-person environment, virtual office hours with faculty should be here to stay, either alone or in combination with in-person office hours, to make faculty more approachable particularly for students who are shy or who feel more like imposters in their field.

Race, Motivation and Belonging in Traditional and ERT Settings

We have discussed how the relationships between key antecedents of belonging such as instructor support and interactions and belonging changed between traditional and ERT learning environments. However, these were not the only differences between the two settings. While belonging among engineering students was not significantly different between traditional learning and ERT (Table 6), the impact of race as a control variable was different between the two settings. Unlike in traditional learning, race was not significantly linked to belonging in ERT. Specifically, in the traditional setting, Asian American students reported less belonging overall and even more so when these students also experience lower levels of self-efficacy in their engineering studies. However, the fact that race does not emerge as a significant predictor of belonging in ERT supports the possibility that despite the stress involved in taking classes in an online format (Casper et al., 2022), the use of online video conferencing tools such as Zoom reduced differences among students from different demographic groups. On Zoom, students could turn off their cameras and could interact with peers and instructors via chat functions rather than voice. Both would reduce opportunities for others to observe or experience racial differences. Moreover, the structural features of online communication forums require using some novel communication patterns in terms of who speaks and when (e.g., it is more difficult for individuals to talk over another speaker because of conflicting microphone assignments). New rules of speaking and conduct are often necessary for teaching and learning via such platforms and therefore can be built into the course by instructors. Such authored structures have been suggested to be effective means for reducing the "silence" of Asian Americans in the classroom (Takeishi, 2008) and may have played an important role in encouraging Asian American students to engage and participate in the online environments during ERT. ERT also caused the suspension of in-person laboratory sessions, which curtailed any in-person peer harassment that may have been occurring in traditional learning settings. Thus, an unanticipated consequence of ERT may have been to provide a safe space where students could interact with instructors and peers without feeling judged for their race and identity.

While race emerged as being significant in traditional classes, the ERT models for belonging highlighted the relevance of motivation as being linked to belonging. Altruism (i.e., choosing engineering as a major for opportunities to benefit society) emerged as a significant motivating factor that was positively associated with belonging both in and of itself (i.e., a main effect) and in interaction with faculty support. Prior research demonstrates mixed results regarding the emergence of altruistic behaviors during situations of existential threats (COVID-19 pandemic). However, there is some theoretical basis to support the emergence of altruistic behaviors during natural disasters (Grimalda et al., 2021). Anecdotally, evidence of students' altruistic behavior was supported during ERT as they used their engineering skills to fight the crisis, step up, and address the needs of the hour. These anecdotes include students volunteering to make masks, working on scalable ventilator devices and measurement systems to estimate viral load, and exploring other engineering solutions to mitigate the impact of the pandemic.

A similar effect was found for students who were motivated to study engineering via a desire to build things. Such students reported greater belonging than was the norm in ERT and appeared to be less sensitive to TA support (Figure 6) than students who were not so motivated. Logically, this might be due to the fact that TA support became more critical to completing laboratories during ERT because students were no longer able to sit side-by-side at the lab bench to consult with their peers. Students who were motivated by building things likely had better hands-on skills than other students and were able to be more self-sufficient during ERT, thus making their belonging less dependent on TA support.

Regardless of why motivation emerged as a contributing factor to belonging in ERT, our results highlight the fundamental role that motivation can play in fostering student belonging in the engineering classroom. As the world moves towards hybrid learning models in the post-ERT environment, new interventions that highlight and value the range of motivations that bring students into the engineering classroom should be considered to promote belonging.

Limitations

All of the participants in this study were from a single, large 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. engineering enrollment (American Society for Engineering Education, 2020). Asian American students were substantially overrepresented (42.7%, vs. 14.7% nationally) and Black students were underrepresented (2.8%, vs. 4.4% nationally). Courses in only two engineering disciplines were included, and these have among the lowest representation of women students. However, the percentage of women in this study's sample (25.0%) slightly exceeded the national average (22.5%) for bachelor's degrees across all engineering disciplines.

Furthermore, this study design is not longitudinal. Each individual participant's data represents a single point in time. Consequently, the direction of causality between variables cannot be determined. Results only confirm correlations. Future work should investigate hypotheses related to causality within a longitudinal dataset. For example, in a traditional classroom setting, frequency of interactions with faculty was negatively associated with belonging, but it would be helpful to know if low belonging inspired students to seek more interaction, or if negative interactions led to lower belonging.

Implications

As we reflect on the impact of the pandemic on students and their education, we must do so with one eye to the future. First and foremost, we found that faculty support, independent of the teaching context, has the strongest connection to belonging. Therefore, moving forward, faculty must play a key role in facilitating students' belonging. Since all educational settings (traditional, remote, and hybrid) are likely to persist, faculty must devise pedagogical strategies for each setting that support students in a constructive, inclusive, and equitable manner. Furthermore, we found that faculty need to exercise caution in their interactions with students, as there is some indication that these interactions can be negatively linked to students' belonging. Because of this, we believe that universities should undertake professional development initiatives that, apart from instructional pedagogy, help faculty develop personal communication styles, policies, etc. that facilitate positive interactions with students which can bolster students' belonging and well-being. The goal is to elevate belonging for *all* students by strategically building a community that is welcoming, inclusive, and supportive to all its members.

In this study, factors that affected students' belonging were fundamentally different in ERT when compared to traditional learning. Importantly, ERT seemed to have leveled the playing field when it comes to racial differences in students' belonging. In ERT, students could comfortably express themselves in a variety of ways without revealing their gender or race and fear of being judged. For example, students who may have been hesitant to speak up in traditional classrooms could use the chat feature during Zoom lectures to express themselves. Further, faculty appeared to have been less intimidating to students during ERT, further reinforcing positive aspects of ERT that can elevate belonging in future hybrid models of teaching.

The results of this study also call for additional investigation into the role of motivation in belonging. Future work should investigate how to design meaningful interactions among students, faculty and TAs that are aligned with what motivates students to pursue engineering. ERT revealed how in a time of crisis, students' sense of altruism was linked to elevated belonging. The goal is to keep that motivation alive long-term through interactions and support. For example, labs and classes could be restructured to capitalize on existing motivations, or extracurricular activities could be designed to more directly speak to students' pre-existing motivations. Therefore, further work on studying motivation in relation to belonging in various engineering classroom settings can help inform how faculty and TAs can facilitate greater student belonging.

Conclusions

This study has examined the relationship between antecedents of belonging in the engineering classroom (peer, TA, and faculty support; interactions with faculty and TAs) and belonging in traditional and ERT settings. The results largely confirm the importance of both support and interactions, consistent with the conceptual framework of belonging based on Baumeister and

Leary's theory of belonging as a fundamental human need (1995), although some important racial, motivational, and online differences have emerged. In traditional learning, Asian American students appear to have a different (and disadvantaged) experience compared to their peers while in ERT settings, belonging among students with altruistic motivations (to benefit society via their choice of major) seems to be less dependent on faculty support than is the case with other students. Further, interactions with faculty and TAs appear to make no difference in belonging in online, ERT settings. While future work may be limited because the ERT setting has largely passed as the global health emergency of COVID-19 has diminished, the results of these and related studies still offer important insight into future hybridized classrooms.

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