

Examining the Impact of Interpersonal Interactions on Course-level Persistence Intentions Among Online Undergraduate Engineering Students

Javeed Kittur, Arizona State University

Javeed Kittur is currently a doctoral student (Engineering Education Systems and Design) at Arizona State University, USA. He received a Bachelor's degree in Electrical and Electronics Engineering and a Master's degree in Power Systems from India in 2011 and 2014 respectively. He has worked with Tata Consultancy Services as Assistant Systems Engineer from 2011-2012, India. He has worked as an Assistant Professor (2014 to 2018) in the department of Electrical and Electronics Engineering, KLE Technological University, India. He is a certified IUCEE International Engineering Educator. He was awarded the 'Ing.Paed.IGIP' title at ICTIEE, 2018.

Dr. Samantha Ruth Brunhaver, Arizona State University

Samantha Brunhaver is an Assistant Professor of Engineering in the Fulton Schools of Engineering Polytechnic School. Dr. Brunhaver recently joined Arizona State after completing her M.S. and Ph.D. in Mechanical Engineering at Stanford University. She also has a B.S. in Mechanical Engineering from Northeastern University. Dr. Brunhaver's research examines the career decision-making and professional identity formation of engineering students, alumni, and practicing engineers. She also conducts studies of new engineering pedagogy that help to improve student engagement and understanding.

Dr. Jennifer M. Bekki, Arizona State University

Jennifer M. Bekki is an Associate Professor in The Polytechnic School within the Ira A. Fulton Schools of Engineering at Arizona State University. Her research interests include topics related to engineering student persistence, STEM graduate students (particularly women), online learning, educational data mining, and the modeling and analysis of manufacturing systems. She holds a bachelor's degree in Bioengineering and graduate degrees in Industrial Engineering, all from Arizona State University.

Dr. Eunsil Lee, Florida International University

Eunsil Lee is a postdoctoral associate at Florida International University in the School of Universal Computing, Construction, and Engineering Education. She received a B.S. and M.S. in Clothing and Textiles from Yonsei University (South Korea) with the concentration area of Nanomaterials and Biomaterials in Textiles. She began her Ph.D. study in Textile Engineering but shifted her path toward Engineering Education, earning her Ph.D. in Engineering Education from Arizona State University. Her research interests center on inclusion in engineering with focuses on students' sense of belonging, faculty and peer interactions, diversity in citizenship, and engineering doctoral education. Prior to her Ph.D., She worked as a research associate at the Korean Institute of Science and Technology, Carbon Composite Materials Research Center.

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Abstract

This research paper examines the influence of interpersonal interactions on the course-level persistence intentions of online undergraduate engineering students. Online learning is increasing in enrollment and importance in engineering education. Online courses also continue to confront issues with comparatively higher course dropout levels than face-to-face courses. This study correspondingly explores relevant student perceptions of their online course experiences to better understand the factors that contribute to students' choices to remain in or drop out of their online undergraduate engineering courses. Data presented in this study were collected during fall 2019 and spring 2020 from three ABET-accredited online undergraduate engineering courses at a large southwestern public university: electrical engineering, engineering management, and software engineering. The data was collected during the pre-COVID time. Participants were asked to respond to surveys at 12-time points during their 7.5-week online course. Each survey measured students' perceptions of course LMS dialog, perceptions of instructor practices, and peer support for completing the course. Participants also reported their intentions to persist in the course during each survey administration.

A multi-level modeling analysis revealed that the Perceptions of course LMS dialog, Perceptions of Instructor Practices, and Perceptions of Peer Support are related to Perceptions of course-level Persistence Intentions. Time was also a significant predictor of persistence intentions and indicated that the course persistence intentions decrease towards the end of the course. A multi-level modeling analysis revealed that LMS dialog, perceptions of instructor practices, and peer support are related to course persistence intentions. Time was also a significant predictor of persistence intentions and indicated that the course persistence intentions decrease towards the end of the course. Additionally, interactions between demographic variables and other predictors (Perceptions of course LMS dialogue, Perceptions of Instructor Practices, and Perceptions of Peer Support) were significant. With the increase in perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support, there was a relatively smaller increase in the persistence intentions of veterans than non-veterans. There is relatively more increase in the persistence intentions of females than males as their perceptions of instructor practices increase. Finally, increasing perceptions of peer support led to a relatively larger increase in the persistence intentions of non-transfer students than transfer students and a relatively smaller increase in persistence intentions of students working full-time than other students.

Introduction

Online education is witnessing an extensive rise in student enrollment [1-2]. Online education also continues to experience higher percentage of dropouts than the in-person face-to-face programs [3-5]. Several reasons for students dropping out from the online courses/programs have been documented, including feeling isolated [6], challenges with balancing academics and personal

demands [7-9], inadequate faculty and peer support [6][9-10], challenges with technology [7][11], and lack of engagement [7][11-12]. Course designs that engage students through course materials and through communications with peers and instructors have been shown to support greater engagement, feeling of connected and belongingness to a part of the community, and enhance persistence rates [12][13-14]. Finally, research also shows that student demographic characteristics such as age, gender, ethnicity, etc. have influenced students' success in online courses [8][15-18].

This study is a part of a larger NSF-funded project studying the persistence of students in online undergraduate engineering courses [19]. The Model for Online Course-Level Persistence in Engineering (MOCPE) framework, posited by this project, includes factors related to course characteristics and individual characteristics [20]. Lee, et al. (2020) gives a complete treatment of the framework [20]. In this paper, we study the impact of interpersonal interactions within the course on persistence intentions of online undergraduate engineering students. In addition, we investigate how this relationship changes as a function of student demographic variables.

Interpersonal Interactions with Instructors and Peers

The virtual distance inherent in online learning environments have been shown to reduce the feelings of sense of belongingness, in turn creating frustration, boredom and feelings of isolation among students [21]. Interpersonal interactions refer to learner-to-learner and learner-to-instructor interactions that take place in the process of both teaching and learning [22-23]. Interpersonal interactions are essential to increase the feeling of belongingness, as these interactions help both the learners and instructors to be connected with the associated community [12].

Instructor-student and student-student interactions have been shown to critically influence student engagement [12][14] [24-25], and interpersonal interactions more generally to influence course satisfaction, instructor satisfaction, students' participation, learning, and persistence rates [13][26-28]. Student motivation and cognitive processes are impacted by both instructor-student and student-student interactions [29]. Conversely, lack of satisfactory interpersonal interactions -- including interactions that are too mandated and too frequent -- have also been shown to generate dissatisfaction and reduced student motivation in online courses [28][30]. Watson et al., [31] found that interactions with peers was influential in helping students in taking the role of active learners and several studies have argued that the lack of interactivity in online courses can be reduced if instructors proactively facilitate interactions and social presence, or feelings connectedness among students [32], in online courses [33-35].

Student-instructor interactions are helpful in nurturing students' interest towards the course content and associated motivations to learn [36]. Martin et al., [37], reported that connecting with the instructor, and instructor's own online presence, were significant in enhancing student engagement and learning. In another study [38], students reported that their engagement in the online learning space was influenced by instructor's behavior and presence in the course. Finally, lack of instructor feedback from the instructor was cited as one of the major reason students chose to drop out of their online course. A study by Ragusa and Crampton [39] revealed that one of the most important forms of communication between instructor and student is quality and timely feedback received.

Being able to easily contact the instructor for feedback has been found to help students feel connected, belonged, and a part of the larger community [40].

Instructor support also plays a significant role in influencing students' decisions about completing or withdrawing from a course. Sorensen & Donovan [9] reported that participants who believed cited not receiving faculty and advisor support as one of the major reasons for discontinuing the study. Another study [10] found that faculty accountability was one of major themes that emerged related to retention issues in online courses.

Peer interactions around course activities such as knowledge exchange and cooperation on projects are important element in online courses; they help foster connections with other students and support belongingness to a community [12][40]. Peer support also has a crucial role in influencing students' persistence decisions in online courses. Robertson [6] found that the absence of course-facilitated peer interaction was frustrating and isolating to students and influenced students' persistence decisions. Similarly, in another study [11] investigating the persistence of students in online courses, in addition to support from family and work, peer support was identified as one of the factors that motivated students to continue and complete the course.

Student Demographic Characteristics

Various student demographic characteristics have been used in the literature to understand how they might relate to student persistence intentions in online courses. In this section, we present information about four student demographic characteristics -- gender identity, transfer students, veterans, employment level -- that are explored in this paper in terms of their relationship to persistence intentions and how those intentions are influenced perceptions of instructor and peer support on these demographic characteristics.

Gender identity is one of the most used demographic variables in research studies that deal with student persistence in online courses. For example, Cochran et al., [16] investigated the influence of different demographic characteristics in predicting student persistence in online courses. The gender identity differences revealed that females were more likely to persist than males. Gender differences have also been found to impact the interactions that take place in online learning environment. For example, Tsai, Liang, Hou, & Tsai, (2015) found that women more actively participated in online discussions than men, and women adapted themselves better in online asynchronous situations [17]. Lin et al., [41] investigated the learner interaction patterns during online collaboration and found no significant differences in degree of participation between men and women. However, the interaction profiles suggested that women in their study were more likely to be cohesive and effective communicators.

Transfer students have been found to be relatively more committed to their engineering programs than the non-transfer students [42]. The institutional culture has also been shown to play a significant role in influencing transfer students' persistence decisions [43]. Incorporating instructor and peer mentoring aspects in online learning environments have shown to enhance the persistence of engineering transfer students [44-45].

Veteran students have been found to be goal-oriented, come with varied useful experiences, motivated, and actively engage in all the assigned learning tasks [18]. Jenner [18] argues that policies, along with formal and informal programs must be used to strengthen the veteran peer communities stronger. Findings from another study [46] showed that interactions with instructors and peers also helped veterans persist academically.

Finally, non-traditional students enrolled in online courses usually are working full- or part-time [47], and students' persistence decisions can be influenced by flexibility in their work schedule and support received from the employer [8][48]. For students managing the extra time commitments of jobs along with school, time management skills can be particularly essential. Underscoring this, Katiso [49] showed a significant relationship between motivation levels of achieving academic goals and time management skills of online students.

Methods

Participants

Eligible participants for this study were students who were enrolled in one of three in three ABET-accredited online undergraduate engineering programs at a large southwestern public university: electrical engineering, engineering management, and software engineering during the fall 2019 and spring 2020 semesters. A total of 152 participants were recruited in this study (96 during fall 2019 and 56 during spring 2020). Table 1 shows the demographic characteristics of the respondents. The sample was 22 percent women, White (71.7%), Asian (2.6%), Hispanic/LatinX (6.6%), Black/African American (3.9%), American Indian or Alaska Native (0.7%), Native Hawaiian or Pacific Islander (2%), and multiple races/ethnicities (1%), 79 percent transfer students, 34 percent first-generation college students, and 29 percent U.S. military veterans. Their ages ranged from 18 to 59 years old ($M=30.4$ years, $SD=7.6$ years). Most participants were employed full-time or part-time (85%) and married or in a committed relationship (66%). About a third of the participants reported having dependent children.

Procedure

An initial screening survey was used to identify participants who were interested and eligible in participating in the survey. The participants for the screening survey were recruited via email who were enrolled in online courses. The screening survey collected three types information (1) current degree and course enrollment (class standing, program, degree, credits, online courses enrolled, etc.) (2) background information (gender identity, race/ethnicity, age, residency status, transfer student status, veteran status, relationship status, parental status, employment status, etc.) (3) contact information and preferred mode of communication (SMS message and/or email address). The gender identity and race/ethnicity related demographic questions were framed following the best practices [50-51]. While responding to the surveys, the participants were assigned with one course out of the different online courses they were enrolled in. Eligible participants were administered a survey packet 12 times ($= 2x / \text{week}$) over a duration of 7.5 weeks, which corresponded to the duration of a single online course at the institution. Participants were given the option to receive survey links at each survey distribution either via text message or email.

Participants were given a total of 48 hours of time to respond to each survey, and a reminder was sent after 24 hours. Students who missed three consecutive surveys or who dropped out from their online courses were dropped from the study. Also, the students who dropped out of the course by themselves were not sent emails/text messages to complete the survey. The participants received \$5 Amazon gift card for completing one survey and \$15 Amazon gift card for completing two surveys. The participants received the Amazon gift cards weekly.

Table 1. Demographic characteristics of the respondents

Category	<i>n</i>	%
Total	152	100
<i>Gender</i>		
Male	117	77
Female	34	22
Genderqueer / Gender non-conforming	01	01
<i>Race/Ethnicity</i>		
American Indian or Alaska native	01	01
Asian	04	02
Black or African American	06	04
Hispanic or LatinX	10	07
Whites	109	72
Multiple races/ethnicities	19	12
Others	03	02
<i>First Generation Student</i>		
Yes	100	66
No	52	34
<i>Transfer Student</i>		
Yes	120	79
No	32	21
<i>U.S. Armed Forces Veteran</i>		
Yes	44	29
No	108	71
<i>Employment Level</i>		
Working full-time	102	67
Working part-time	27	18
Not working	23	15
<i>Dependent Children</i>		
Yes	54	36
No	98	64
<i>Relationship status</i>		
Single/Never married	45	29
Separated, divorced, or widowed	06	04
Married	74	49
In a committed relationship	26	17
Prefer not to say	01	01

Instruments

The survey package that participants completed at each survey administration was the MOCPE instrument, which is detailed in Lee, et al. (2020). [20]. The MOCPE instrument contains scales

defined and designed to measure student perceptions about course characteristics, student characteristics and course-level persistence intentions. In this study, we use the data from course characteristics and course-level persistence intentions. The course characteristics include perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support. The perceptions of course LMS dialog scale captures student perceptions about the students' opportunity for dialog with others (instructor and peers) and has four items. The perception of instructor practices scale measures student perceptions of their instructor's behavior class management practices within the online environment. The perception of instructor practices scale had eight items in total. Finally, the four-item perception of peer support scale measures the perceptions of support students receive from peers and feeling of connectedness in the course. For more details on each of these scales the readers are directed to reference paper [20].

The internal consistency reliability was calculated for each of the 12 survey distributions in fall 2019 and each of the 12 survey administrations during spring 2020. Table 2 shows the associated range of Cronbach's α values, all of which indicate that suitable internal consistency reliability was achieved.

Table 2. Range for Cronbach's α over 12 surveys

Variables	Cronbach's α	
	Fall 2019	Spring 2020
Course LMS dialog	0.927 – 0.965	0.879 – 0.990
Instructor practices	0.927 – 0.960	0.891 – 0.963
Peer support	0.900 – 0.943	0.872 – 0.964
Persistence intentions	0.866 – 0.962	0.888 – 0.982

Data Cleaning and Analysis

Using SPSS, the scale scores were calculated by averaging the relevant items scores, this was done for all the 12 survey administrations separately. Participants with missing data were removed from this analysis. No missing survey question responses are present in the data reported here; however, there are cases where participants did not respond to entire survey packet administrations. Unique response IDs were assigned to each of the participants from both fall 2019 and spring 2020, and all the independent continuous variables in the final structure of the data were grand mean centered (GMC). The final structure of the data was formatted as shown in Table 3.

Multi-level Modeling Analysis

Multi-level modeling (MLM) was used to analyze the longitudinal data in this study. To explore the variations of students' course persistence intentions in online undergraduate engineering courses, a null model with zero predictors was built. To examine an individual student's growth in the course persistence intentions over time and to investigate the need to test the model with other predictors, time was considered as a predictor in the model. Different models were built by including one predictor in addition to the predictor time, to understand the relationships between students' course persistence intentions and other independent variables considered in this study. The demographic variables race/ethnicity (underrepresented minority student status), parental

status, relationship status, and first-generation student status among others were examined and were found to be not statistically significant.

Table 3. Structure of the final data

ID	Time	Persistence intentions	LMSdialog_GMC	Instructor_GMC	Peer_GMC	Gender	Veteran	Transfer student
1205	0	4.6	0.68	1.43	0.61	0	1	0
1205	1	4.6	0.93	1.43	0,76	0	1	0
1205	2	4.6	0.93	0.91	0,76	0	1	0
-	-	-	-	-	-	-	-	-
1205	10	4.6	1.43	0.69	0.61	0	1	0
1205	11	4.6	0.86	0.91	-0.15	0	1	0
1480	0	4.8	0.67	-0.11	0.88	1	0	1
1480	1	4.8	0.79	0.73	0,63	1	0	1
1480	2	4.8	-1.30	0.68	0.44	1	0	1
-	-	-	-	-	-	-	-	-
1480	10	4.8	-1.30	-0.11	-0.19	1	0	1
1480	11	4.8	0.94	0.63	-0.19	1	0	1
1621	0	4.0	0.45	1.56	1.67	0	1	0
1621	1	4.0	0.77	0.65	1.67	0	1	0
1621	2	4.0	0.98	0.23	0.62	0	1	0
-	-	-	-	-	-	-	-	-
1621	10	4.0	1.21	1.56	0.58	0	1	0
1621	11	4.0	-0.95	0,45	0.18	0	1	0

Note. gender: 0-male, 1-female; veteran; 0-No, 1-Yes; transfer student: 0-No, 1-Yes

To further understand the influence of one independent variable on the other, interactions were considered with different combinations in different models. More specifically, the following research questions will be addressed in the study, (1) What is the relationship between students' course persistence intentions and their perceptions of course LMS dialog in online undergraduate engineering courses? (2) What is the relationship between students' course level persistence intentions and perceptions of instructor practices in online undergraduate engineering courses? (3) What is the relationship between students' course persistence intentions and perceptions of peer support in online undergraduate engineering courses? For each of these three questions, we also explore whether the relationships are different for different gender identities, for traditional vs. non-traditional (i.e., veteran and/or transfer student status) students, and for employment level.

Results

Multi-level Modeling Analysis

The variations of students' course persistence intentions in online undergraduate engineering courses was examined by building a null model with zero predictors. The output of the null model suggests that the variation in the course persistence intentions is statistically significant ($p < 0.001$), and a mixed model could be built to further explore the associations of this persistence intentions variable with other predictors. Time was considered as a predictor to determine students' variations in course persistence intentions over time and to examine the need of building other models using different predictors. The variations in the course persistence intentions over time is statistically significant ($p = 0.001$), which implies that there are differences in students' course persistence

intentions at different time points during their course and the persistence intentions decrease as students move along in their courses. This allows further testing of the model by including other predictors.

As shown in Table 4, three multi-level models were built to under the association of course persistence intentions with three different predictors (perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support). From Table 5, it is evident that time is statistically significant across all the three models ($p=0.003$, $p=0.019$, $p=0.001$). In other words, students' course persistence intentions vary across the 12 time points and there is decrease in persistence intentions as the course progresses towards completion. The perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support are all statistically significant ($p<0.001$, for all three cases). This implies that, student's course persistence intentions increase with increase in positive perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support.

Table 4. Multi-level models (Dependent variable: persistence intentions)

Model 1				Model 2				Model 3			
Parameter	β	SE	p	Parameter	β	SE	p	Parameter	β	SE	p
Intercept	4.64	0.04	0.000	Intercept	4.62	0.04	0.000	Intercept	4.65	0.04	0.000
Time	-0.02	0.01	0.003	Time	-0.01	0.01	0.019	Time	-0.02	0.01	0.001
LMS dialog	0.08	0.02	0.000	Instructor practices	0.2	0.02	0.000	Peer support	0.12	0.02	0.000

Note. Model 1 – independent variables: time and perceptions of course LMS dialog

Model 2 – independent variables: time and perceptions of instructor practices

Model 3 – independent variables: time and perceptions of peer support

Table 5 shows the multi-level modeling results of seven models built with persistence intentions as the dependent variable, and perceptions of course LMS dialog, time, and demographic variables as the independent variables. All these models included an interaction term between two variables, the perceptions of course LMS dialog and the demographic variables. Empty cells in the Table 6 (filled with hyphens (-)) imply that those specific variables were not a part of the model under study. In all the seven models, perceptions of course LMS dialog and time were statistically significant. That is, the score on the student's persistence intentions increase with increase in the score on the perceptions of course LMS dialog, and there is a decrease in the score on the student's persistence intentions over time during the course. The demographic variables gender, underrepresented minority student status, first generation students, transfer student status, veteran student status, and employment level were not statistically significant. However, the variable parental status was statistically significant ($\beta=0.17$, $p=0.049$), which means that students with children reported higher score on the persistence intentions than students without children. The demographic variable veteran was not statistically significant, however, the interaction between course LMS dialog and veterans was statistically significant ($\beta=-0.1$, $p=0.005$). The interaction plot describing this interaction is shown in Fig 1. From the interaction plot it can be concluded that, with increase in score on the perceptions of course LMS dialog scale, there is little change in the persistence intentions of veterans. However, with increase in the score on the perceptions of course LMS dialog, the increase in the score on the persistence intentions of non-veterans is relatively more.

Table 5. Multi-level modeling results (Dependent variable: persistence intentions, Independent variable: LMS dialog, time, and demographic variables)

Parameter/Model	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	β	SE	β	SE	β	SE	β	SE	β	SE	B	SE	β	SE
Intercept	4.62*	0.13	4.65*	0.04	4.69*	0.07	4.65*	0.09	4.6*	0.05	4.57*	0.07	4.58*	0.05
dialog	0.12***	0.05	0.08*	0.02	0.08**	0.03	0.11*	0.03	0.12*	0.02	0.11*	0.03	0.09*	0.02
time	-0.02**	0.01	-0.02**	0.01	-0.02**	0.01	-0.02**	0.01	-0.02**	0.01	-0.02**	0.01	-0.02**	0.01
gender	0.02	0.09	-	-	-	-	-	-	-	-	-	-	-	-
dialog*gender	-0.03	0.04	-	-	-	-	-	-	-	-	-	-	-	-
underrepresented minority (URM)	-	-	-0.04	0.1	-	-	-	-	-	-	-	-	-	-
dialog*URM	-	-	0.004	0.04	-	-	-	-	-	-	-	-	-	-
first gen. student	-	-	-	-	-0.07	0.09	-	-	-	-	-	-	-	-
dialog*first gen. student	-	-	-	-	0.007	0.04	-	-	-	-	-	-	-	-
transfer	-	-	-	-	-	-	-0.01	0.1	-	-	-	-	-	-
dialog*transfer	-	-	-	-	-	-	-0.04	0.04	-	-	-	-	-	-
veteran	-	-	-	-	-	-	-	-	0.12	0.09	-	-	-	-
dialog*veteran	-	-	-	-	-	-	-	-	-0.1**	0.04	-	-	-	-
employment	-	-	-	-	-	-	-	-	-	-	0.11	0.09	-	-
dialog*employment	-	-	-	-	-	-	-	-	-	-	-0.05	0.04	-	-
parental status	-	-	-	-	-	-	-	-	-	-	-	-	0.17***	0.08
dialog*parental status	-	-	-	-	-	-	-	-	-	-	-	-	-0.05	0.04

Note. * $p < 0.001$, ** $p < 0.01$, *** $p < 0.05$, β – estimate, SE – standard error

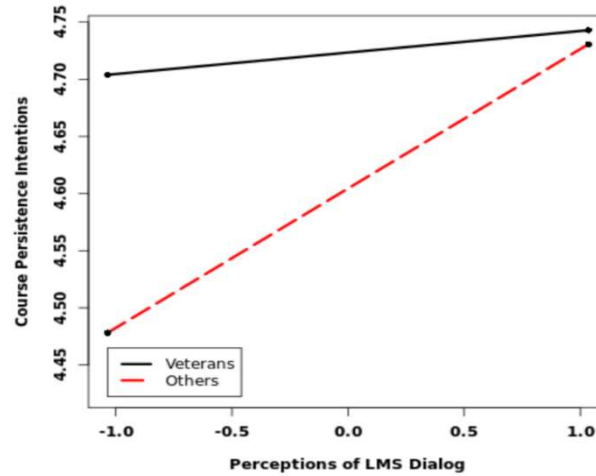


Fig 1. Interaction effect between course LMS dialog and veterans

Table 6 shows the multi-level modeling results of seven models built with persistence intentions as dependent variable, perceptions of instructor practices, time, and demographic variables as the independent variables. All these models included an interaction term between two variables, the perceptions of instructor practices and the demographic variables. In all the seven models, perceptions of instructor practices and time were statistically significant. That is, the score on the student's persistence intentions increase with increase in the score on the perceptions of instructor practices and as described previously, there is decrease in the score on the student's persistence intentions over time during the course. The demographic variables gender, underrepresented minority student status, first generation students, transfer students, and veterans were not statistically significant. However, the variables employment status and parental status were statistically significant ($\beta=0.17, p=0.035$; $\beta=0.16, p=0.049$). That is, students working full-time reported higher score on the persistence intentions than other students, and students with children reported higher score on the persistence intentions than students without children. The demographic variables gender identity and veteran student status were not statistically significant by themselves; however, the interactions between instructor practices and gender identity, and instructor practices and veterans were statistically significant ($\beta=-0.18, p<0.001$; $\beta=-0.1, p=0.029$). The interaction plot for the same are shown in Figs 2(a) and 2(b). From Fig 2(a), it can be concluded that, with increase in the score on the perceptions of instructor practices, there is a relatively greater increase in the score on the persistence intentions of women than men. From Fig 2(b), it is observed that, with increase (or decrease) in perceptions of instructor practices there is relatively less increase (or decrease) in persistence intentions of veterans than other students.

Table 7 shows the multi-level modeling results of seven models built with persistence intentions as dependent variable, perceptions of peer support, time, and demographic variables as the independent variables. All these models included an interaction term between two variables, the perceptions of peer support and the demographic variables. In all the seven models, perceptions of peer support and time were statistically significant. That is, the score on the student's persistence intentions increase with increase in the score on the perceptions of peer support and as described previously, there is decrease in the score on the student's persistence intentions over time during the course. The demographic variables gender identity, underrepresented minority student status, first generation student status, transfer student status, veteran student status, and employment level were not statistically significant. However, the variable parental status was statistically significant ($\beta=0.17, p=0.044$). That is, students with children reported higher persistence intentions than students without children. The demographic variables transfer student status, veteran student status, and employment status were not statistically significant by themselves, however, the interaction between peer support and transfer student status, interaction between peer support and veteran student status, and interaction between peer support and employment level were statistically significant ($\beta=-0.23, p<0.001$; $\beta=-0.2, p=0.018$; $\beta=-0.1, p=0.034$). The interaction plot for the same are shown in Fig 3(a), 3(b) and 3(c). From Fig 3(a), it can be concluded that, with increase in the score on the perceptions of peer support, there is relatively more increase in the score on the persistence intentions of the non-transfer students than transfer students. From Fig 3(b), it is observed that, with increase in the score on the perceptions of peer support there is relatively less increase in the score on the persistence intentions of veterans than other students.

Table 6. Multi-level modeling results (Dependent variable: persistence intentions, Independent variable: instructor practices, time, and demographic variables)

Parameter\Model	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
Intercept	4.55*	0.12	4.62*	0.04	4.67*	0.07	4.59*	0.08	4.59*	0.05	4.5*	0.07	4.57*	0.05
instructor practice	0.43*	0.06	0.2*	0.02	0.21*	0.04	0.31*	0.04	0.23*	0.02	0.24*	0.03	0.22*	0.02
time	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01
gender	0.05	0.09	-	-	-	-	-	-	-	-	-	-	-	-
instructor practice*gender	-0.18*	0.05	-	-	-	-	-	-	-	-	-	-	-	-
underrepresented minority (URM)	-	-	0.02	0.09	-	-	-	-	-	-	-	-	-	-
instructor practice*URM	-	-	-0.02	0.05	-	-	-	-	-	-	-	-	-	-
first gen. student	-	-	-	-	-0.08	0.08	-	-	-	-	-	-	-	-
instructor practice*first gen. student	-	-	-	-	-0.01	0.05	-	-	-	-	-	-	-	-
transfer	-	-	-	-	-	-	0.03	0.09	-	-	-	-	-	-
instructor practice*transfer	-	-	-	-	-	-	-0.14	0.05	-	-	-	-	-	-
veteran	-	-	-	-	-	-	-	-	0.11	0.08	-	-	-	-
instructor practice*veteran	-	-	-	-	-	-	-	-	-0.1***	0.04	-	-	-	-
employment	-	-	-	-	-	-	-	-	-	-	0.17***	0.08	-	-
instructor practice*employment	-	-	-	-	-	-	-	-	-	-	-0.07	0.04	-	-
parental status	-	-	-	-	-	-	-	-	-	-	-	-	0.16***	0.08
instructor practice*parental status	-	-	-	-	-	-	-	-	-	-	-	-	-0.07	0.05

Note. * $p < 0.001$, ** $p < 0.01$, *** $p < 0.05$, β – estimate, SE – standard error

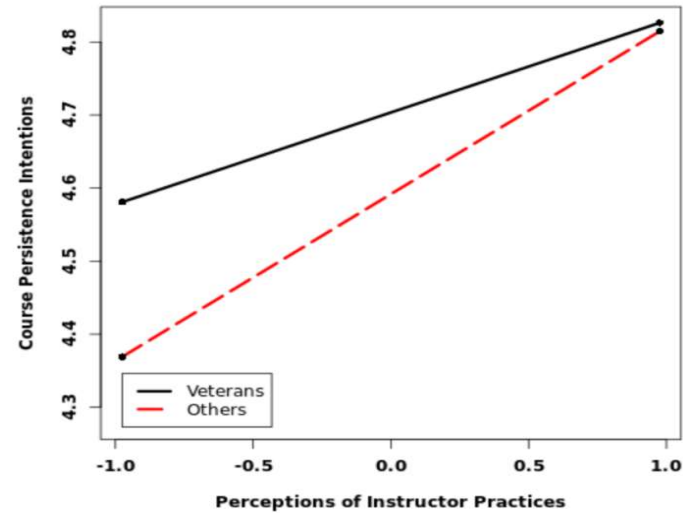
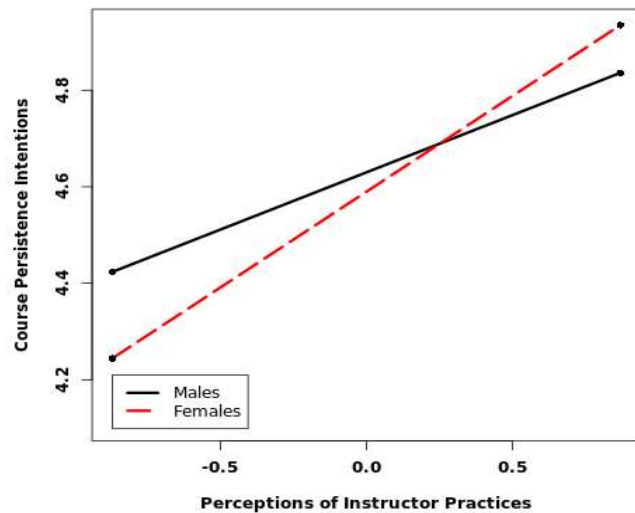


Fig 2(a) and 2(b). Interaction effect between instructor practices and gender, instructor practices and veterans

Table 7. Multi-level modeling results (Dependent variable: persistence intentions, Independent variable: peer support, time, and demographic variables)

Parameter\Model	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
Intercept	4.59*	0.12	4.65*	0.04	4.71*	0.07	4.62*	0.08	4.61*	0.05	4.55*	0.07	4.59*	0.05
peer support	0.19*	0.07	0.12*	0.02	0.15*	0.04	0.29*	0.04	0.15*	0.02	0.18*	0.04	0.14*	0.03
time	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01
gender	0.04	0.09	-	-	-	-	-	-	-	-	-	-	-	-
peer support*gender	-0.06	0.05	-	-	-	-	-	-	-	-	-	-	-	-
underrepresented minority (URM)	-	-	-0.02	0.1	-	-	-	-	-	-	-	-	-	-
peer support*URM	-	-	-0.04	0.05	-	-	-	-	-	-	-	-	-	-
first gen. student	-	-	-	-	-0.09	0.08	-	-	-	-	-	-	-	-
peer support*first gen. student	-	-	-	-	-0.06	0.04	-	-	-	-	-	-	-	-
transfer	-	-	-	-	-	-	0.03	0.09	-	-	-	-	-	-
peer support*transfer	-	-	-	-	-	-	-0.23*	0.05	-	-	-	-	-	-
veteran	-	-	-	-	-	-	-	-	0.12	0.09	-	-	-	-
peer support*veteran	-	-	-	-	-	-	-	-	-0.12***	0.05	-	-	-	-
employment	-	-	-	-	-	-	-	-	-	-	0.15	0.08	-	-
peer support*employment	-	-	-	-	-	-	-	-	-	-	-0.1***	0.05	-	-
parental status	-	-	-	-	-	-	-	-	-	-	-	-	0.17***	0.08
peer support*parental status	-	-	-	-	-	-	-	-	-	-	-	-	-0.07	0.05

Note. * $p < 0.001$, ** $p < 0.01$, *** $p < 0.05$, β – estimate, SE – standard error

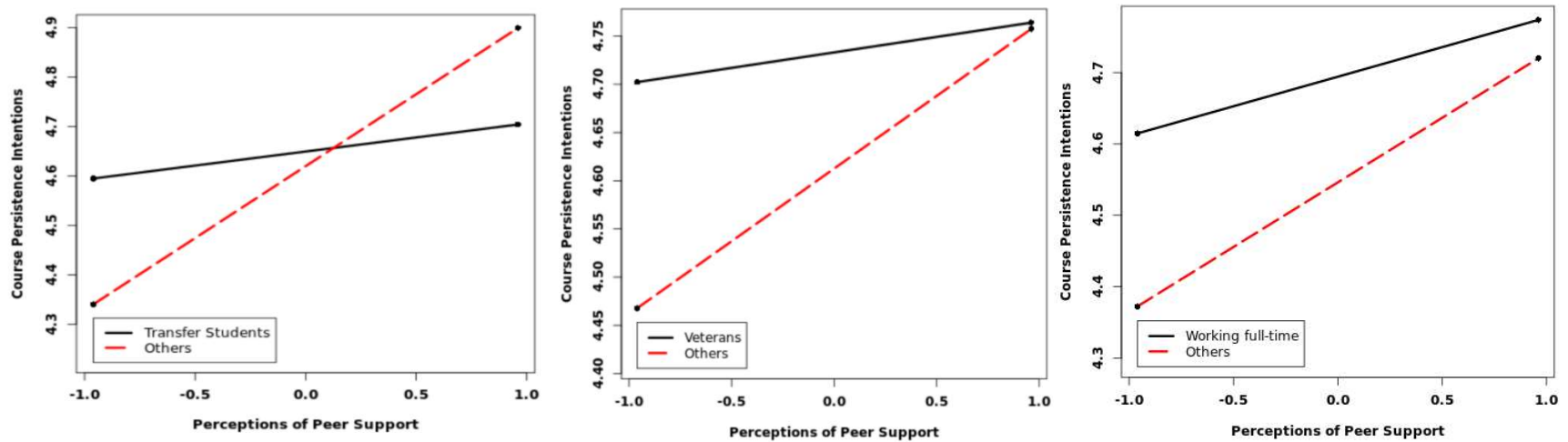


Fig 3(a), 3(b) and 3(c). Interaction effect between peer support and transfer students, peer support and veterans, peer support and employment status

From Fig 3(c), it is implied that, with increase in the score on the perceptions of peer support there is relatively less increase in the score on the persistence intentions of students working full-time than other students.

Discussion

The results from this study suggest that, interpersonal interactions in online courses are important as they influence student's persistence decisions. A significant relationship between course-level persistence intentions and the perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support was found through the multi-level modeling analysis. These findings make sense given that both instructor-student and student-student interactions have been shown to critically influence student engagement [12][25-25], which is linked to persistence [26][52-54].

The investigation of relationship between persistence intentions and interpersonal interactions as a function of the student demographic characteristics revealed that significant interaction effects exist. Women reported significantly higher increase in course-level persistence intentions than men with increase in positive perceptions of instructor practices. This finding aligns with Cochran et al., [16] who investigated the influence of different demographic characteristics in predicting student persistence in online courses and found that women were more likely to persist than men. In another study designed to examine the gender differences, it was reported that women actively participated in online discussions and women adapted themselves better in online asynchronous situations in comparison with men [17].

Without the peer support, transfer students reported higher course-level persistence intentions than non-transfer students. As per the literature, transfer students are focused, and they generally show higher commitment levels towards the assigned tasks. For example, Litzler & Young (2012), found that transfer students were found to be relatively more committed to their engineering programs than the non-transfer students [42]. On the other hand, with increase in peer support, non-transfer students reported higher course-level persistence intentions than transfer students. Similar findings were reported in the study [15], where the transfer student's success was not completely influenced by the peer- and instructor-interactions, however, interactions with advisors was reported to be of help in successfully completing the program. On the contrary, various studies have shown that incorporating instructor and peer mentoring aspects in online learning environments [44-45] could improve the persistence of engineering transfer students.

Veterans have reported higher score on the course-level persistence intentions than other students when they reported lower scores on the perceptions of LMS dialogue, perceptions of instructor practices, and perceptions of peer support scales. This finding aligns with the fact that veterans are goal-oriented, they come with varied useful/valuable experiences, motivated, and they actively engage in all the assigned learning tasks [55]. With increase in the score on the perceptions of course LMS dialog, instructor and peer support services, veterans have reported higher score on

the persistence intentions than other students. This finding is like that reported in the study [46], that interactions with instructor and peers helped veterans persist academically.

Students working on a full-time basis reported higher course-level persistence intentions than other students. The expectations of time and energy on different jobs is different, some more demanding than the other. Hence being able to manage time to complete the required tasks both course and work related are essential. For examples in studies [7][11], management of time was found to be an important factor which could facilitate persistence as well come across as a barrier in completing online courses. With increase in support from the peers, an increase in the score on the course-level persistence intentions was observed in students working full-time than others. However, there was relatively less increase in the persistence intentions of students working full-time than others with increase in the score of the perceptions of peer support.

Conclusions, Limitations, Implications and Future Work

A multi-level modeling analysis was carried out to investigate the relationship between course-level persistence intentions of online undergraduate engineering students, time, and three dimensions of online interactions (perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support). In addition, investigation of how this relationship changes as a function of different student demographic variables (gender identity, transfer student status, veteran student status, underrepresented minority student status, first-generation student status, and employment status) was presented.

Like any other study, this study also comes with limitations. The sample considered in this study was not a representative of all the online engineering education community, as we recruited participants from one university, and only undergraduate students. Additionally, we are unable to provide information about the reasons behind any of the findings presented, as we are limited to the data collected in our survey instruments.

The results from this study suggest that institutions focusing on improving the student persistence in online undergraduate engineering programs (and other online programs) must consider interpersonal interactions in online courses as an essential element. Specifically, course instructors with the flexibility in designing courses can bring considerable changes in the students' learning experiences in online courses by intentionally including opportunities for students to interact with the content, peers, and instructor.

Next steps for this work will include recruiting participants from online engineering institutions around the country, as well as including students at differing higher educational levels (e.g., undergraduates and graduate students). We will also conduct qualitative research studies to further investigate the findings obtained in this study; we are particularly interested in understanding the "why" behind the findings presented here. More specifically, we'd like to gather data to help shed light on how students of differing demographic identities perceive interpersonal interactions in

their online courses (e.g., the quality and importance of those interactions) and to what extent these interactions influence their persistence decisions.

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