Understanding Factors Influencing Online Undergraduate Engineering Students' Persistence Decisions

by

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ABSTRACT

Online education is fast growing due to its accessibility and scalability, but engineering has fallen behind other fields in adopting and researching the online educational format. Student course-level attrition is a significant issue in online courses. The goal of this dissertation is to better understand the factors that impact course level persistence decisions among online undergraduate engineering students. Three different research methodologies were employed for this study: a systematic literature review (SLR), learning analytics and data mining, and multi-level modeling.

The SLR focuses on understanding the temporal trends and findings from research in online engineering education. A total of thirty-nine articles published between 2011 to 2020 met inclusion criteria, and the synthesis of these articles revealed five themes: content design and delivery, student engagement and interactions, assessment, feedback, and challenges in online engineering. Theoretical, methodological, and publication trends across the forty articles were also summarized.

Data for the second study was compiled from 81 courses contained within three online, ABET-accredited undergraduate engineering degree programs at a large, public institution in the southwestern United States. The students' learning management system (LMS) interaction data was utilized to create features that represent the amount of time students spent on different course activities and how those times differed from "typical" interaction patterns among students in the same course. Association rule mining was used to develop rules that describe the behavior of students who completed the course (i.e., completers) and those who opted to withdraw (i.e., leavers). The best measure of student engagement was determined to be the mathematical difference between the percentages of completer and leaver rules met by each student.

Finally, multi-level modeling was used to examine the impact of interpersonal interactions on online undergraduate engineering students' course-level persistence intentions. The data for this study was gathered from online courses during the 2019-2020 academic year. Students completed questionnaires about their course and related persistence intentions twelve times during their 7.5-week online course. Students' perceptions of the course LMS dialog, instructor practices, and peer support were found to significantly predict their course persistence intentions.

DEDICATION

I would like to dedicate my dissertation to God, my parents, my wife, and my son, who have always supported me in my personal and professional decisions, specifically when I made the decision to pursue Ph.D. at Arizona State University. I could not have achieved this major milestone without their support and motivation.

ACKNOWLEDGMENTS

Well, I would like to share a brief story that landed me at Arizona State University. When I started my teaching career in academic year 2014-2015, I came across *Indo Universal Collaboration for Engineering Education* (IUCEE) and happened to enroll in the *IUCEE International Engineering Educator Certification Program* (IIEECP). I completed this program with distinction and had tremendous learning in this program, however, lesser known to myself, I was exploring my newfound interest in engineering education research (EER) during the certification program. After completing the certification program, I had the multiple opportunities to interact with Dr. Gopalkrishna Joshi who made me realize my interest in EER and guided me to the best possible opportunities to pursue my Ph.D. in engineering education.

I would like to thank Dr. Ashok Shettar and Dr. Gopalkrishna Joshi for introducing me to Dr. Sohum Sohoni and the wonderful EESD program at ASU. After interacting with Dr. Sohoni and getting to know more about the EESD program, I learned that EESD at ASU was the place for me to pursue my Ph.D. I would like to thank Dr. Sohoni and Sheetal Sohoni for always being there for me just a phone call away. I still remember the Skype call I had with Dr. Jennifer Bekki in late 2017, she was then serving as the chair of the EESD program, Dr. Bekki was kind in answering all my questions and she made me feel welcomed and comfortable, and eased my decision of choosing ASU for my Ph.D.

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CHAPTER 1

DISSERTATION OVERVIEW

As seen by the growing number of enrollments, online education is gaining global recognition and acceptance because it provides several benefits such as flexibility, scalability, and accessibility (Allen, Seaman, Poulin, & Straut, 2016; Seaman, Allen, & Seaman, 2018). Despite these benefits, engineering has been significantly slower to embrace and investigate the online learning format than other disciplines. One of the most significant issues in online education is student course attrition, which is greater in online courses than in face-to-face classes (Bowers & Kumar, 2015; Shea & Bidjerano, 2016; Gregori, Martínez, & Moyano-Fernández, 2018). This dissertation research, Understanding Factors Influencing Online Undergraduate Engineering Students' Persistence Decisions, looks at factors impacting students to persist and successfully complete the courses versus dropping out from a course. For this study, three investigations were used, each with a distinct research approach: a systematic literature review, learning analytics and data mining, and multi-level modeling.

The first study was a systematic literature review (SLR) that provides an overview of the study themes, research gaps, and recommendations for future work present in current scholarship on online engineering education (see Chapter II). Thirty-nine conference and journal articles published between 2011 and 2020 were reviewed for this analysis. Findings revealed five themes: content design and delivery, engagement and interactions, assessment, feedback, and challenges in online engineering courses. Theoretical, methodological, and publication trends across the thirty-nine articles were summarized as well.

The second and third studies in this dissertation address a specific need raised in the SLR for more research on *student engagement and interactions*. The second research study (see Chapter III) addresses the lack of field consensus on the best technique to measure student engagement in their online courses. It presents a metric for undergraduate engineering students' online course engagement based on data detailing their interactions with an online course learning management system (LMS) using data mining and learning analytics. Data from 81 courses offered by three fully online, undergraduate engineering degree programs generated a total of 3,848 unique student–course combinations (approximately 2.7 million rows of LMS interaction data), to which a five-step process was applied to calculate a single score representing student LMS engagement. First, the students' LMS interaction data were converted into a set of natural features representing the time they spent per three-day period on various course elements, such as quizzes, assignments, discussion forums, and so forth, and how these times changed across the duration of the course. The natural features were then used to derive 216 relative features describing deviations from typical interaction patterns among students in the same course. Next, association rule mining was conducted on a training portion of the data set to generate rules separately describing the behavior of students who completed the course (completers) and those who chose to drop early (leavers). The rules generated were applied to students from the testing portion of the data set to compute the percentage of unique rules met by completers and leavers. Finally, the best measure of student engagement was determined to be the mathematical difference between the percentages of completer and leaver rules met by each participant.

The third research study (Chapter IV) expands on the SLR study's concept of "student engagement and interactions." This study looked at the influence of interpersonal interactions on the course-level persistence intentions of online undergraduate engineering students. In this study, interpersonal interactions were operationalized as students' perceptions of (1) the ability of their course LMS to facilitate dialog, (2) the peer support available in their courses, and (3) the practices used by the instructor in their courses. Interactions between students' demographic characteristics and each of these measures of interpersonal interactions were also explored. Over the course of 7.5 weeks, 152 students enrolled in three ABET-accredited online engineering programs completed 12 surveys. Students' perceptions of the course LMS dialog, peer support, and instructor practices in their online course were measured in each survey, along with students' intentions to complete the course. Perceptions of course LMS dialog, instructor practices, and peer support were found to influence students' course-level persistence intentions, based on a multi-level modeling analysis. 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. Three main findings emerged specifically: (1) The impact of perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support on course-level persistence intentions was smaller for veteran than for non-veteran students. (2) The impact of perceptions of instructor practices on course-level persistence was smaller for men than for women students. (3) The impact of perceptions of peer support on course-level persistence intentions was smaller for transfer than for non-transfer students, and for students working full-time than for other students. The results point to the need for further research to understand how students of differing demographic identities perceive the quality and importance of interpersonal interactions in their online courses and to what extent these interactions influence their persistence intentions.

CHAPTER 2

TRENDS IN ONLINE ENIGINEERING EDUCATION – A SYSTEMATIC LITERATURE REVIEW

1. Overview

Online engineering education is gaining increasing acceptance and recognition globally due to its benefits of accessibility, flexibility, and scalability. Prior research in online education has shown that it has enormous benefits for a wide range of students and learners. However, engineering has been slower to adopt and investigate the online educational format than other fields. This paper presents a systematic literature review on research in online engineering education, with the goal of examining current knowledge related to this topic and supporting future scaling efforts. A total of thirty-nine publications between 2011 to 2020 made it to the final synthesis phase of our review process. These studies were classified under seven themes: content design and delivery, student engagement and interactions, assessment, feedback, and challenges in online engineering courses. Findings related to each theme and their associated implications for research and practice are discussed in the paper.

2. Introduction

Because of its accessibility, flexibility, and scalability, online education is fast growing (Allen, Seaman, Poulin, & Straut, 2016; Seaman, Allen, & Seaman, 2018), with rising enrollments representing a clear pathway for increasing the size and diversity of the engineering workforce. However, while the number of online course and program offerings for engineering students has gradually expanded over the last decade (Seaman, Allen, & Seaman, 2018), engineering has been much slower to adopt and investigate the online educational format than other disciplines. Further, student course-level attrition remains greater in the online format than in face-to-face courses (Bowers & Kumar, 2015; Shea & Bidjerano, 2016; Gregori, Martnez, & Moyano-Fernández, 2018), which limits the number of online students earning engineering degrees. There is, therefore, a need to investigate the limitations and opportunities surrounding online engineering education to better support future scaling efforts.

A systematic literature review on the trends and current state of knowledge arising from research on online engineering education was conducted to specifically address this need. Findings from this review provide a summary of the main topics studied in the online engineering education space, connections between these topics, gaps in the research, and recommendations for future work. Together, these findings serve to increase awareness and capacity for online engineering education research and catalyze effective practices for online engineering teaching and learning. The following research sub-questions were used for exploration and categorization of the articles under review:

1. What is the distribution of sampled articles by:
    a. year of publication?
    b. publication type and publication outlet?
    c. country of affiliation of the first author?
    d. engineering disciplines included?

2. What among the sampled articles are the most frequently used:
    a. theoretical frameworks?
    b. research foci and research design?
    c. sampling methods and range of sample sizes?
    d. study populations and participant demographics?
3. What among the sampled articles are the most common:
    a. themes, trends, or patterns in the findings?

Importantly, a survey of the available literature revealed studies pertaining to a broad range of online course formats including fully online courses, hybrid courses, and massive online open courses (MOOCs) offered either independently from or as part of a formal engineering curriculum. MOOCs differ from online courses offered as part of a formal engineering curriculum in that they usually are open to anybody, require no formal academic preparation or approval, and employ different assessment methods mostly automated grading including multiple choice-questions (Sezan & Sevim Cirak, 2020; Staubitz et al., 2020). Hence, we chose to restrict their review to fully online courses offered as part of a formal engineering curriculum. Articles on all other kinds of online engineering education that did not meet these criteria were excluded.

Positionality

I have always been fascinated by online engineering education. As a student, I have been a user of an online learning management system platform as a part of an online course; as an instructor, I have designed and taught online courses; and as a researcher, I have read considerable literature over the past three years in the online engineering education space. Together, these experiences have informed my beliefs that looking at research on online engineering education from a global perspective and understanding the applicability of online learning to diverse courses and programs within engineering disciplines is essential. Additionally, they have motivated me to investigate the different frameworks used in research on online engineering education, with the intention of proposing new frameworks for use in the online learning space. They have also interested me in exploring the research and practice implications arising from research on online engineering education, particularly as they relate to improving students' experiences and connections with their peers and instructors. These positionalities guided the inquiry and interpretations made in this portion of my dissertation.

3. Methods

The systematic literature review process involves entering different search terms into a variety of databases (Borrego, Foster, & Froyd, 2014; Clapton, Rutter, & Sharif, 2009; James, Randall, & Haddaway, 2016). A total of eight search terms were used in this study: online engineering courses, online engineering persistence, online STEM persistence, online engineering retention, online engineering effectiveness, online engineering engagement, online engineering assessments, and online engineering challenges. One of the major challenges in online engineering education in comparison with face-to-face courses is the higher dropout rate, and hence, the search terms online engineering persistence, online engineering retention, and online STEM persistence were selected. The nine different databases used to find articles were ProQuest, Google Scholar, IEEE Xplore Digital Library, ERIC (Education Resources Information Center), Science Direct, Compendex, Wiley Online Library, EBSCOhost, and Scopus. Nine exclusion criteria (EC) were defined to eliminate articles that did not fit the purpose of the study. The article selection process for the systematic literature review is presented in Figure 1. The articles retrieved from these databases and those that made it to the final synthesis phase after review were all journal or conference papers.

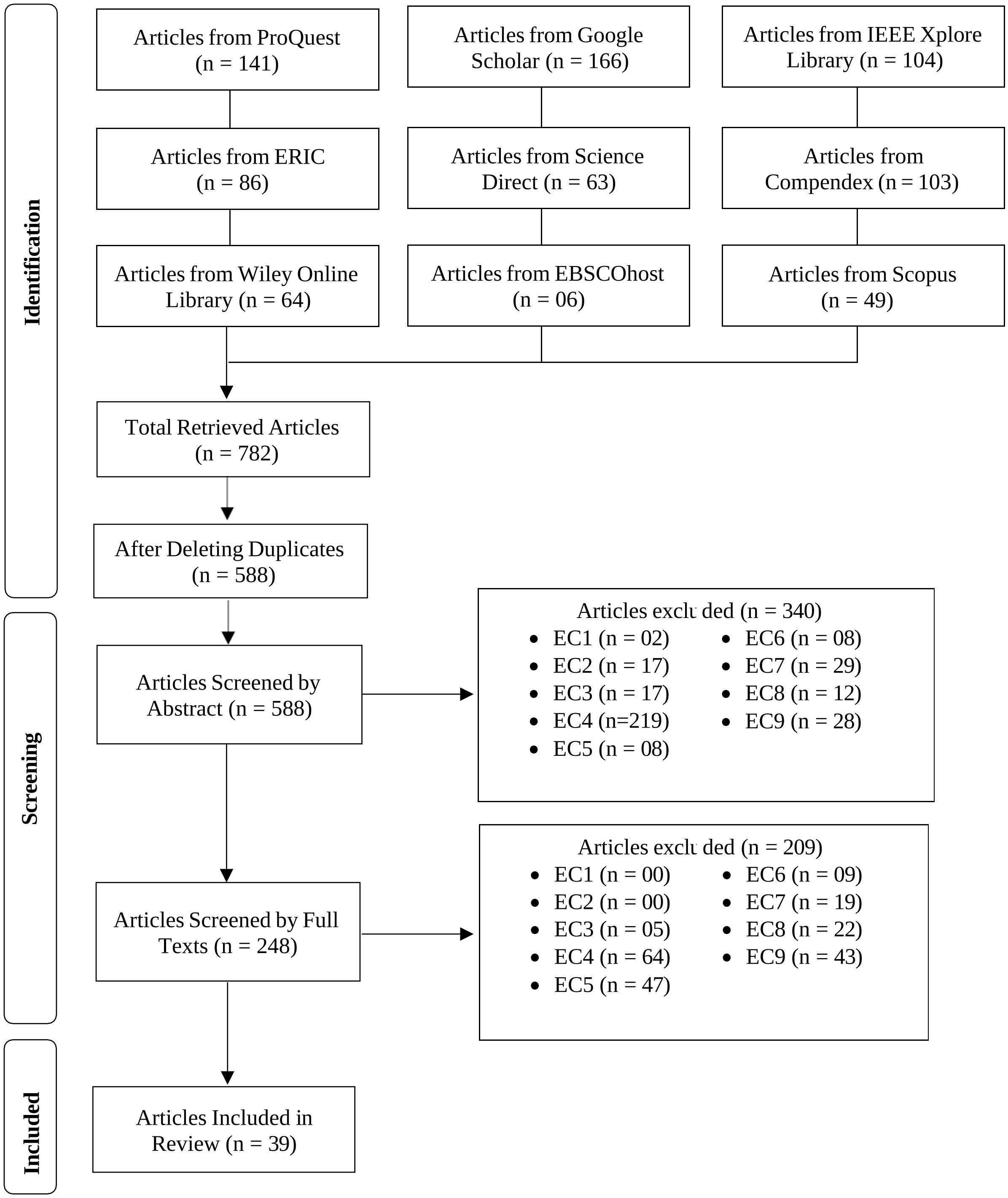

Figure 1: Systematic Literature Review – Article Selection Process

3.1 Exclusion Criteria

EC1. Articles were published in a language other than English.

EC2. Articles were not published between 2011 and 2020.

EC3. Articles were not full-length papers, i.e., work-in-progress publications and short length papers are excluded from this study since the details presented in such articles are insufficient to draw solid conclusions.

EC4. Articles contained no focus on online engineering.

EC5. Articles focused on synchronous online teaching and learning (e.g., via Zoom).

EC6. Articles focused on Massive Online Open Courses (MOOCs).

EC7. Articles focused on transitioning a face-to-face course to an online or hybrid course due to the COVID-19 pandemic.

EC8. Articles focused on blended learning in which some elements of the course were taught face-to-face and other elements of the course were taught online, such as in flipped-classroom pedagogy.

EC9. Articles focused on how a specific component of the course (e.g., assignment, assessment, activity) was planned and executed online, with the remainder of the course being taught in person or insufficient detail about the specifics of the course (i.e., whether the course is taught face-to-face or online, etc.) provided.

3.2 Data Collection and Analysis

A total of 782 articles were retrieved using the eight search phrases and nine databases listed above. Then, articles were excluded by the first reader to remove duplicates from various databases (194 articles) and to eliminate articles that superficially met the exclusion criteria (EC1 to EC9) based on scrutiny of abstracts (340 articles) and complete texts (180 articles). Thirty of the remaining 68 articles (approximately one-half) were evaluated independently for inclusion by the first and second readers. Disagreements about whether to include two of the articles were resolved through discussion. In total, seventeen of the thirty articles met the exclusion criteria and were removed from consideration, leaving 51 articles. The first reader then reevaluated all 51 articles against the exclusion criteria, eliminating an additional twelve. Thirty-nine articles remained for the final synthesis phase of the review.

The final synthesis phase was conducted by the first and second readers following a six-step process. First, a set of fifteen articles was read meticulously by both readers to consolidate information addressing the research sub-questions in a Microsoft Excel file. This Excel file was used to capture the following information for each article: year of publication, publication type and publication outlet, engineering discipline and courses, country affiliation of the first author, theoretical frameworks used, research foci and research methods, study populations and participant demographics, sampling methods and range of sample sizes, and research findings. The Excel files from both readers were compared to confirm that the records were consistent and that no discrepancies were observed. Second, codes describing common patterns across the fifteen articles were identified, and a codebook with the definition and examples for each of fourteen parent codes was generated. Third, a second set of fifteen articles was reviewed by both readers to capture information addressing the research questions in the Excel file and either map each article to the fourteen parent codes generated in the previous step or, if an article could not be mapped to the existing codes, propose new codes. Fourth, the codes generated in the second and third steps were further analyzed and grouped to create themes, leading to five emergent themes related to online engineering courses: content design and delivery, student engagement and interactions, assessment, feedback, and challenges. Fifth, Cohen's Kappa measure of agreement was used to determine inter-rater reliability between the two readers to assess the dependability of the analysis, resulting in a Cohen's Kappa of κ = 0.88, where a score of .81 to 1.00 indicates near- perfect agreement (Landis & Koch, 1977). Lastly, the first reader captured information addressing the research questions and assigned one or more of the five emergent themes to each of the nine remaining articles.

Data analysis in this paper is presented in two parts. The first phase examines the trends in the thirty-nine articles retained for final investigation using descriptive statistics. These results are reported as tables, line charts, and graphs. The second part presents the qualitative analysis of the thirty-nine articles, depicting the current state of knowledge arising from research on online engineering education over several themes.

4. Strengths and Limitations

This systematic literature review provides a holistic picture of research on online engineering education by assessing the trends and current state of knowledge in the field. Each theme generated as part of this study is complemented by implications for both practice and research meant to provide instructors and researchers in the online engineering education space with specific actionable guidance. The findings of this study greatly expand understanding of research in the field of online engineering education. Based on our evaluation of the literature, no other systematic literature review on the topic exists.

This research, like all studies, has certain limitations. First, articles were selected based on exclusion criteria that did not include a metric of quality or uniqueness of information therein. Since quality is sometimes indirectly related to the publication outlet and reviewing standards, we hope that this limitation was at least partially mitigated by obtaining articles from nine separate and highly reputable databases, which increased the likelihood of finding all the research in the literature that would be considered unique and high quality. Second, the search terms used in this study focused on the intersection of online education, engineering, and specific areas of interest such as assessment or persistence. It seems possible that articles and themes relevant to the systematic review might have emerged using different combinations of these and other words, as four of the seven themes were the same or similar to the search terms. Third, the articles published after 2020 were not included in the systematic review. Fourth, this systematic review may not cover the entire landscape of online engineering education as there may be courses or programs that practitioners and researchers might find interesting or relevant that have not been published. Fourth, in alignment with other systematic literature reviews within engineering education (e.g., Anwar et al., 2019; Borrego et al., 2018; Sezgin & Sevim Cirak, 2021; Verdin, Godwin, & Capobianco, 2016), we used nine databases that we expected to contain a large number of journal and conference articles focused on online engineering education research. However, we did not include books or other technical reports in our search, which may have limited the scope of information covered within the SLR. Finally, as the articles were limited only to English, they may have only captured a narrow portion of the global scholarship on online engineering education.

5. Findings

This section addresses the research sub-questions that guide this systematic review. First, trends in the following over the last decade are presented: number of publications by year, publication types and outlets, distribution of articles based on country affiliation of first author, engineering disciplines and courses, theoretical frameworks, research foci and research methods, study populations and participant demographics, and sampling methods and range of sample sizes, are presented. Second, descriptions, exemplar studies, and research and practice implications are provided for each of seven themes that emerged from synthesis of the final thirty-nine articles.

5.1 Trends in publication by year

From 2011 through 2020, there was a general increase in the number of articles published on online engineering education research per year, reaching a high in 2020 (Fig 2). This trend is encouraging because it suggests a proliferation of interest in the online learning format by engineering scholars and practitioners in their research and teaching, respectively.

5.2 Publication Type and Publication Outlet

Conference papers and journal articles constituted the articles used in this study. The thirty-nine articles reviewed for this study were published as conference proceedings (69%) and journal articles (31%), respectively. One of the arguments supporting this finding could be that conferences have relatively shorter review cycles/times than journals which allows more timely sharing of work. Most conference papers sampled in this systematic review were published in conferences sponsored by the American Society for Engineering Education (ASEE) (48%) and the Institute of Electrical and Electronics Engineers (IEEE) (22%), with the remainder published in other venues. Further, the journal articles sampled in this study appeared in the following journal outlets: *Computer Applications in Engineering Education* (25%), *Education and Information Technologies* (8.3%), *Advances in Engineering Education* (8.3%), *Chemical Engineering Education* (8.3%), *IEEE Transactions on Education* (8.3%), *IEEE Transactions on Learning Technologies* (8.3%), *Internet and Higher Education* (8.3%), *Journal of Online Engineering Education* (8.3%), *Sustainability* (8.3%), and *Online Learning* (8.3%).

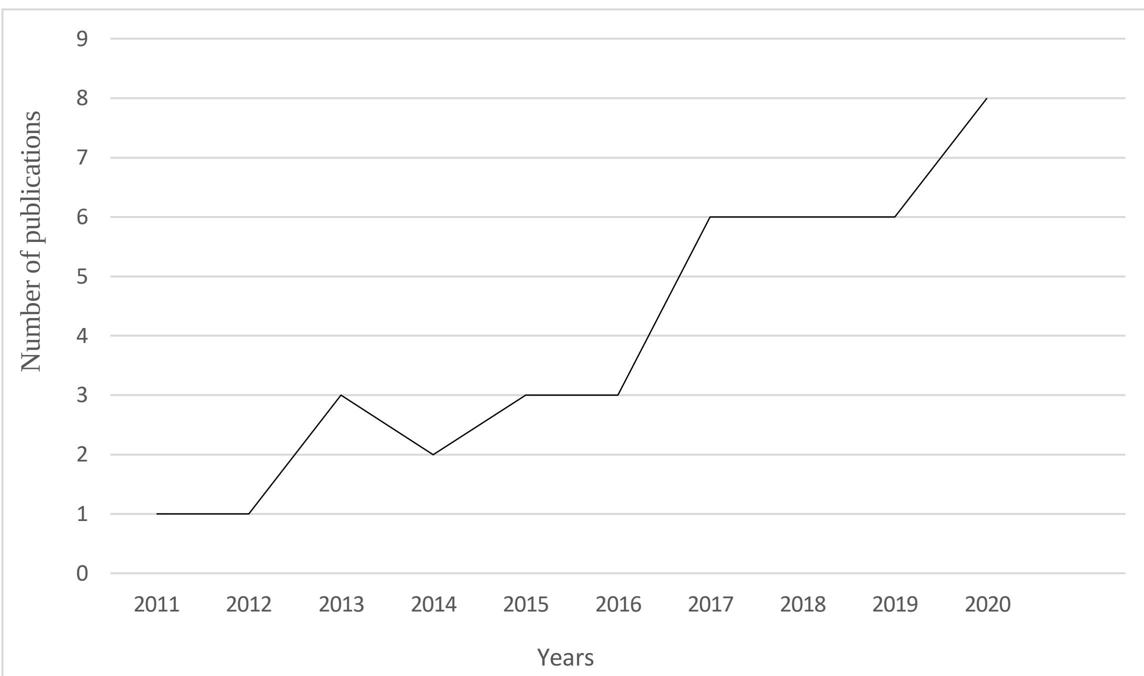

Figure 2: Time Trend Series of Sampled Publications

5.3 Country Affiliation of First Author

Table 1 shows that the articles selected for this review featured first-authors from fourteen distinct countries. The majority of first authors heralded from the U.S. (53.9%), followed by Spain (12.8%), Australia (5.1%), and each other country (2.6%). The articles that were chosen as the sample were from 14 different countries. The findings suggests that the center of gravity for online engineering education research resides within the U.S. and this argument could be potentially based on the fact that we included articles written only in English. Also, practitioners in other countries could be engaging and investing in online engineering education but not have the same pressure, incentives, or engineering education research infrastructure to publish on this work as in the U.S.

Table 1. Distribution of Country of Affiliation of First Author

#	Country	Frequency	Percentage (%)
1	United States	21	53.9
2	Spain	5	12.8
3	Australia	2	5.1
4	Greece	1	2.6
5	Japan	1	2.6
6	Ireland	1	2.6
7	Malaysia	1	2.6
8	Morocco	1	2.6
9	Portugal	1	2.6
10	Romania	1	2.6
11	Germany	1	2.6
12	Turkey	1	2.6
13	United Arab Emirates	1	2.6
14	Canada	1	2.6

5.4 Engineering Disciplines and Courses

Table 2 lists the engineering disciplines and courses studied in the thirty-nine articles analyzed for this review. Across all fields, Mechanical Engineering (13.3%) was the most often studied discipline across the articles, followed by Computer and Telecommunications Engineering (13.3%), Engineering Management (10.0%), First-Year Engineering (6.7%), Systems Engineering (6.7%), and each other discipline (3.3%). Further, the courses studied span undergraduate and graduate courses, in addition to theory-based and laboratory-based courses. These findings indicate the applicability of online learning to diverse courses and programs within engineering. (Note: nine articles in the sample are not included in Table 2 – these articles comprise of literature reviews as well as general online engineering-based studies wherein specific disciplines or courses were not indicated).

5.5 Theoretical Frameworks

Fifteen articles used a theoretical framework, nine articles used conceptual framework grounded in the literature, and the remaining fifteen articles did not use a framework in their study. For papers that did employ a theoretical framework, the frameworks they cited using are summarized in Table 3. Notably, no frameworks were repeated across these studies, indicating an opportunity for further testing and application of each one of these existing frameworks in the online engineering learning space. However, while none of the frameworks repeated, at least three of articles discussed the same three factors (peers, faculty, and environment) important for online student engagement (Fu, 2019, Odom et al., 2019, Rutz & Ehrlich, 2016). Five of the fifteen articles that did not use a framework were literature reviews, for which a framework is typically not used. The remaining articles that did not use a framework discussed the design of a new course or new interventions within a course.

Table 2. Disciplines and courses of sampled articles

#	Discipline	N	%	Courses	N	%
1	Mechanical Engineering	4	13.3	- Computer Aided Engineering	1	3.4
				- Engineering Dynamics	1	3.4
				- Introduction to Natural Sciences	1	3.4
				- Strength of Materials	1	3.4
				- Thermodynamics	1	3.4
2	Computer and Telecommunications Engineering	4	13.3	- Cognitive Network Design *	1	3.4
				- Digital Design	1	3.4
				- Mathematical Analysis	1	3.4
				- Mathematics II	1	3.4
3	Engineering Management	3	10.0	- Operations Management *	1	3.4
				- Technology Planning and Management *	1	3.4
4	First-year Engineering	2	6.7	- Support Program in Mathematics	1	3.4
5	Systems and Control Engineering	2	6.7	- All courses program-wide *	1	3.4
				- Lab Practices on Instrument. and Control *	1	3.4
6	Aerospace Engineering	1	3.3	- Mechanics of Materials	1	3.4
7	Chemical Engineering	1	3.3	- Core Chemistry Concepts I *	1	3.4
				- Core Chemistry Concepts II *	1	3.4
8	Computer Science	1	3.3	- Operating Systems	1	3.4
				- Signals and Systems	1	3.4
9	Computing, Engineering, and Management of Information Systems	1	3.3	- Courses not indicated	1	3.4
10	Electrical and Computer Engineering	1	3.3	- Electrical Circuits	1	3.4
				- Introduction to Electrical Laboratory	1	3.4
11	Engineering Science	1	3.3	- Learning from Engineering Disasters	1	3.4
12	Informatics Engineering	1	3.3	- Software Development Laboratory	1	3.4
13	Manufacturing Systems Engineering	1	3.3	- All courses program-wide *	1	3.4
14	Marine Engineering	1	3.3	- English Academic Course for Engineering	1	3.4
15	Discipline Not Indicated	6	20.0	- Economic Decision Making *	1	3.4
				- Effectiveness in Technical Organizations *	1	3.4
				- Info. Management and Data Engineering	1	3.4
				- Intercultural Engineering	1	3.4
				- Thermoelectricity *	1	3.4
				- Product Data Management	1	3.4

Note: * denotes the inclusion of graduate courses

Table 3. Theoretical frameworks used in sampled articles

#	Framework(s)	Reference article
1	Backward design, Bloom's taxonomy	Chatterjee et al., 2016
2	Community of Inquiry (CoI) Model	Rutz & Ehrlich, 2016
3	Constructivism	Minichiello et al., 2013
4	Inquiry-based Learning	Uribe et al., 2016
5	Social Influence Theory	Schutz, Kim, & Dionne, 2018
6	Systems Engineering-based Framework	Bozkurt & Helm, 2013
7	Trifecta of Engagement	Fu, 2019
8	Skills in e-learning courses	Levy & Ramim, 2017
9	Bloom's taxonomy	Pamplona et al., 2018
10	Motivational frameworks (expectancy x value theory, four phase model of interest, multiple goals model)	Cooper et al., 2020
11	Self and co-regulation of learning	Pedrosa et al., 2020
12	Problem based learning	Andersson & Logofatu, 2018
13	Kolb learning styles	Mansor & Ismail, 2012
14	Self-regulation theory	Sancho-Vinuesa et al., 2018
15	Theories of formative assessment	Lawton et al., 2012

5.6 Research Foci and Research Methods

Table 4 summarizes the different research foci and methods used in the sample articles. Five kinds of articles emerged from the set: literature reviews (12.8%), articles focused on the description of new or existing courses (33.3%), articles focused on the description of new or existing interventions (30.8%), articles focused on the description of new or existing programs (5.1%), and more fundamental research that transcends specific courses and programs (17.9%). (Note: studies marked as “no research” were descriptive and did not include original data collection and analysis).

Table 4. Research foci and research approach in sampled articles

#	Research foci	N	%	Research methods	N	%
1	Literature review	5	12.8	No research (descriptive)	5	12.8
2	Course description	13	33.3	No research (descriptive)	3	7.7
				Qualitative	2	5.1
				Quantitative	4	10.3
				Qualitative and quantitative	4	10.3
3	Intervention description	12	30.8	No research (descriptive)	1	2.6
				Qualitative	1	2.6
				Quantitative	4	10.3
				Qualitative and quantitative	6	15.4
4	Program description	2	5.1	No research (descriptive)	2	5.1
5	Fundamental research	7	17.9	Quantitative	5	12.8
				Qualitative and quantitative	2	5.1

The five identified literature reviews in online engineering education cover topics including the teaching of online laboratory courses (Badjou & Dahmani, 2013), the measurement of quality online education (Danaher, 2014), holistic online instructional design (Kiridena et al., 2014), sustainability challenges in online engineering education (Perales Jarillo et al., 2019), and the prevention of academic cheating in online courses (Siddhpura & Siddhpura, 2020). Importantly, while several of these literature reviews were published nearer to the beginning of our screening window (2011-2020), many of these articles' findings remain as relevant to online engineering education today as almost a decade ago.

The thirteen articles with focus on a new or existing course tended to use both qualitative and quantitative research methods. The qualitative studies under this category collected open-ended student responses or instructor reflections about their course perceptions and experiences. Likewise, the quantitative studies under this category surveyed students about their course perceptions, while studies mixing qualitative and quantitative methods collected student perception data, as well as student course performance and student teacher evaluation data. Five of the eight studies utilizing quantitative or mixed methods reported descriptive statistics only; the remaining three included simple inferential statistical tests in their analyses. For example, van de Vegte (2017) used Wilcoxon signed ranks tests to evaluate changes in student perspectives of intercultural engineering due to participation in an online intercultural engineering course; findings revealed positive increases in their perceptions of humanitarian engineering and intercultural teamwork.

The twelve studies focused on interventions skewed more heavily quantitative in their research methods. Five of these studies present interventions related to feedback and assessment, whereas the other seven describe new tools and technologies embedded into the classroom or laboratory. Data collected in these studies include: (1) open-ended and survey responses related to students' perceptions about the course, the intervention, and gains in their conceptual understanding; (2) student course performance and completion data; and (3) student usage and interaction data (e.g., with the instructor). Of the ten studies employing quantitative or mixed methods, six used inferential statistical analyses to evaluate the effectiveness of their intervention on students. For example, Batanero et al. (2019), Sancho-Vinuesa et al. (2018), and Uribe et al. (2016) employed Wilcoxon signed ranks tests, ANOVA, and paired t-tests to compare changes in student performance (e.g., grades, test scores) before and after implementing their interventions, respectively.

Two of the thirty-nine articles reviewed for this study focused on program design or improvement. One paper detailed the development of a master's level program in manufacturing systems engineering (Badurdeen et al., 2015). The other described the implementation of a course equivalence program that allows students in a master's level systems engineering program to fulfill their degree requirements with course credit from other institutions (Zhang, 2020). Both papers were descriptive in nature, containing no student or instructor data.

Lastly, seven articles focused on what we define as “fundamental research,” i.e., research that transcends specific courses or programs to increase general knowledge related to online engineering education. All papers in this category included a quantitative component to their data collection and analysis and tended to employ more advanced statistical techniques. E.g., Chen et al. (2018) and Hachey et al. (2015) identified determinants of student satisfaction and pass rate using linear and logistic regression, respectively. Further, papers falling under this category also were more likely to use institutional, programmatic, or instructor-based data to support their analyses. Odom et al. (2019) and Schutz et al. (2018) leveraged U.S. News & World Report data and rankings on top U.S. institutions with online engineering master’s programs to identify programmatic determinants of institutional student engagement score and institutional percentage of enrolled student veterans. Hammout and Hosseini (2020) used programmatic enrollment data to demonstrate differences in gender representation across master’s level graduate programs, including engineering. Levy and Ramim (2017) investigated 46 instructors’ opinions about the skills students require to persist and succeed in online engineering courses. In sum, the articles in this systematic review cover a wide range of research foci and methods, with more quantitative methods present in the area of fundamental research.

5.8 Study Populations and Participant Demographics

Table 5 shows the study populations included among the thirty-nine papers in this systematic review. Twelve (50.0%) studied only undergraduate student populations, five (20.8%) studied only graduate student populations, three (12.5%) studied both undergraduate and graduate student populations, one (4.2%) studied employees in the workforce, and three (12.5%) studied student populations but did not specify their academic level (undergraduate or graduate). Further, two papers (5.1%) featured instructors as their population, while another two papers (5.1%) featured U.S. institutions with online master's engineering programs as their population. The remaining eleven papers in the review (28.9%) did not include original research or, therefore, participant data (refer to "no research" categories in Table 8).

Table 5. Distribution of study populations in sampled articles

Study population	**N**	***%***	**Study subpopulation**	**N**	**%**
Students	24	61.5	Undergraduate only	12	50.0
			Graduate only	5	20.8
			Undergraduate and graduate	3	12.5
			Employees in workforce	1	4.2
			Unknown	3	12.5
Instructors	2	5.1	-		
Institutions	2	5.1	-		
Not applicable (not research)	11	28.2	-		

Of the 24 articles featuring student populations, just nine (37.5%) reported information about students' demographic backgrounds. All nine reported students' gender identities, four reported students' racial and ethnic identities, and four reported students' ages. The remaining fifteen (65.2%) did not report any of the participants' demographic information. These findings highlight the need for greater reporting of demographic information when presenting online engineering education research involving students; such information would allow for better contextualization and understanding of specific student experiences related to online learning.

5.9 Sampling approaches and sample sizes

Table 6 and Table 7 summarize the sampling approaches and sample size ranges utilized across the thirty-nine publications reviewed for this study. Table 6 illustrates that most studies of online engineering education appear to be based on data from a single course, while Table 7 shows that approximately as many studies have sample sizes in the 1 to 50 sample range as in the 51 to 300+ sample range.

Table 6. Sampling approaches employed in sampled articles

Sampling approaches	**N**	**%**
Single course	18	46.2
Multiple courses	5	12.8
Multiple institutions	5	12.8
Not applicable (not research)	11	28.2

Table 7. Sample sizes employed in sampled articles

Sampling sizes	**N**	**%**
1-50	13	33.33
51-150	5	12.8
151-300	3	7.7
301 and more	4	10.3
Not indicated	3	7.7
Not applicable (not research)	11	28.2

To help further contextualize these findings, Table 8 presents the sampling methods and sample sizes for the studies referenced above, categorized by research foci (refer to Table 4). (Note: sample size ranges in Table 8 are based on studies for which sample sizes were indicated.) The results reveal a tendency for studies about courses and interventions to draw data from just one course and, as such, to rely on smaller sample sizes. Alternatively, data for fundamental research in online engineering education tend to come from multiple (more than 2) courses and/or institutions, from which larger datasets needed to conduct the associated analyses (e.g., regression modeling) are available. These findings suggest (1) a potential to expand the generalizability of results from single courses and interventions by engaging instructors from other courses, programs, and institutions in replication and extension studies and (2) the need for more fundamental research in online engineering education to expand current knowledge to beyond what we can learn from isolated efforts.

Table 8. Sampling methods and sample sizes by research foci

Research foci	N	%	Sampling method	N	%	Sample size: range (median)
Course description	10	25.6	One course	9	90.0	10 – 175
			Multiple courses	1	10.0	(35)
Intervention description	11	28.2	One course	9	71.8	1 – 2,047
			Multiple courses	2	18.2	(25)
Fundamental research	7	17.9	Multiple courses	2	28.6	46 – 5,000
			Multiple institutions	5	71.4	(136)
Not applicable (not research)	11	28.2				

6. Themes

A total of eleven codes were generated from the review of articles: assessment, feedback, attrition or enrollment, class design or structure, content delivery, engagement, laboratory design, learning technology, pedagogical considerations, technical challenges, and time challenges. These codes, their description, and exemplars of each code are presented in Appendix B. Table 9 shows how these codes were mapped to each theme. Table 9 also summarizes the number of articles (*N*) categorized under each theme, with ten articles categorized under more than one.

In this section, we explore each theme in depth. We introduce the theme, explain how the articles grouped under the theme relate to the theme, present two exemplar studies chosen for their complete and direct connection to the theme, and conclude with a summary of the implications of the theme for future research and practice.

Table 9. Distribution of sampled articles based on thematic classification

Themes	**Definition**	**Codes**	***N***
Content design and delivery	Topics related to content design of online courses, pedagogies implemented in online format, and the delivery of educational content online through different formats. These online courses could be fundamental and/or laboratory courses in online engineering.	class design and structure content delivery laboratory design pedagogical considerations	21
Student engagement and interactions	Topics describing student engagement throughout the course, interactions between students, interactions between students and instructors, and interactions of students with the course content in online engineering courses.	engagement learning technology	6
Assessment	Topics related to course assessments including quizzes, assignments, exams, projects, etc. in online engineering courses. Other topics include assessment of students' conceptual knowledge, misconceptions, and academic misconducts in online engineering courses/programs.	assessment	8
Feedback	Topics related to different types of feedback including feedback from the instructor to students using different approaches (e.g., text-based, interactive, or automated feedback), and student feedback about the instructor's teaching approaches and the overall course.	feedback	5
Challenges in online engineering	Topics that discuss challenges related to time management, technical issues, enrollment, retention, or persistence in online engineering courses/programs.	time challenges technical challenges attrition or enrollment	9

6.1 Theme 1: Content Design and Delivery

Twenty-one articles addressed the important elements of online engineering course design and delivery. Together, these articles highlight that teaching courses online is different from teaching courses in the face-to-face format and, hence, adequate attention must be given to course design and delivery to leverage the online modality fully. Fourteen articles under this theme can be categorized as describing the design and delivery of online fundamentals courses (e.g., Balagiu & Sandiuc, 2020; Bir & Ahn, 2017; Bozkurt & Helm, 2013; Chen, Bastedo, & Howard, 2018; Fatehiboroujeni, Qattawi, & Goyal, 2019; Kiridena, Samaranayake, & Hastie, 2014; Minichiello, Legler, Hailey, & Adams, 2013; Purwar & Scott, 2019; van de Vegte, 2017). Specific foci of studies under this category included the development of new supportive technology for blind and deaf engineering students (Batanero et al., 2019), the incorporation of learning about engineering disasters in a multidisciplinary online course (Halada, 2017), the analysis of a support distance learning program in mathematics (Matzakos & Kalogiannakis, 2018), the implementation of simulation-based programming to promote self and co-regulated learning (Pedrosa et al., 2020), and the use of instructional videos in an online engineering economics course (Pohl & Walters, 2015).

An additional five articles under this theme can be categorized as describing the design and delivery of online laboratory courses (Andersson & Logofatu, 2018; Astatke, Scott, & Ladeji-Osias, 2011; Badjou & Dahmani, 2013; de la Torre et al., 2020; Uribe, Magana, Bahk, & Shakouri, 2016; Zhang, 2020). These studies cover the use of computational simulations (Badjou & Dahmani, 2013; Uribe et al., 2016), problem-based learning (Andersson & Logofatu, 2018), remote or virtual laboratories (Astatke, Scott, & Ladeji-Osias, 2011; Badjou & Dahmani, 2013; de la Torre et al., 2020), home kits (Badjou & Dahmani, 2013), and blended or residential lab experiences (Badjou & Dahmani, 2013) as methods for providing online students access to laboratory experiments. Lastly, two articles (Badurdeen et al., 2015; Zhang, 2020) discussed the design and implementation of new systems engineering degree programs.

6.1.1 Exemplar Studies

Exemplar studies under the theme of content design and delivery highlight the importance and use of videos in online engineering fundamentals courses. One such study is Purwar and Scott (2019) who presented the design, development, and implementation of an online sophomore-level engineering dynamics course. The course was offered over a six-week period as eight modules, each containing eight to ten videos explaining course concepts and problem-solving approaches. Each video was available to students on the course learning management system and accompanied by formative quizzes based on the material covered in the video. In addition, each module included homework assignments and summative quizzes that contributed to students' grades. Students were given opportunities to interact (ask questions and/or discuss) with peers and the instructor using a web-based forum called Piazza. In another exemplar study, Pohl and Walters (2015) explored the use of instructor-developed videos to teach Economic Decision-Making to engineering graduate students. In the course, lecture videos provided an introduction, motivation, and theoretical background for course content, while tutorial videos included working example problems. The instructor made available to students 63 videos with average length 11.6 minutes to ensure that each video was not too long. The authors argued that posting lectures and tutorials as separate videos reduced the length of each video, made the purpose of each video clearer, and thereby helped students better understand the content in each video.

Exemplar studies under the content design and delivery theme also showcase the use of technology and problem-based and collaborative learning pedagogies in online engineering laboratory courses. For example, Astatke, Scott, and Ladeji-Osias (2011) discussed using Mobile Studio Technology to provide electrical and computer engineering students with the opportunity to conduct laboratory experiments online. The first laboratory experiment familiarized students with the Mobile Studio Board hardware and software. Subsequent laboratory experiments required students to design, compute, simulate, analyze, and submit reports of their findings. Students also had to demonstrate to the instructor their design and circuit for each experiment using Adobe Connect software. Separately, Andersson and Logofatu (2018) applied problem-based learning to an Introduction to Natural Sciences laboratory course in mechanical engineering. In this course, students were divided into groups of four and asked to solve chemistry-related problems using a seven-step process. Students communicated with members of their group through chat forums, web conferences, and email to solve each problem. Feedback from the students indicated that they were enthusiastic about the application of problem-based learning in the lab and sincerely completed all the assigned tasks.

6.1.2 Research Implications

Pohl and Walters (2015) demonstrated that keeping instructional videos as separate lecture and tutorial videos helps students understand course material better. A potential direction for future research could be to determine how learners perceive instructional videos categorized as lectures and tutorials and what aspects of these videos help them best engage with the course content and enhance their learning. Additionally, effective course design influences student learning in both face-to-face and online modalities. Hence, further efforts in this direction are needed. Examining the relevance and applicability of the approaches (laboratories using simulations, remote laboratories, home kits, and blended or residential lab experiences (Badjou & Dahmani, 2013) to teach different engineering topics can aid in designing and developing approaches that best suit those topics. Additionally, considering the reduced opportunities for students to interact with peers and instructor in online courses as compared with traditional face-to-face courses, more research into the skillsets required for an instructor to successfully teach online courses and the strategies to meaningfully adopt curriculum design, delivery, and assessment to the online format is necessary.

6.1.3 Practice Implications

The studies classified under this theme offer six practice implications for instructors designing online engineering fundamentals and laboratory courses. First, instructors are encouraged to incorporate the following six elements into their course design: (1) clear teaching roles and expectations, (2) use of a learning management system (LMS) platform, (3) integrated assessment and feedback, (4) integrated opportunities for student accountability, (5) integrated opportunities for student involvement and participation, and (6) a safe environment for discussion (Fatehiboroujeni, Qattawi, & Goyal, 2019; Halada, 2017; Purwar & Scott, 2019). Second, instructors can embed quizzes (or another form of assessment) in online videos to monitor if students are viewing the videos, assess their conceptual knowledge, and enable students to reflect on their learning (Purwar & Scott, 2019). Third, instructors can keep instructional videos short and focused, use effective visual slides, include both audio and video of the instructor, and provide an introductory overview of the video content (Pohl & Walters, 2015). Lastly, instructors can ensure that online laboratory courses are low cost to the student, do not compromise student learning, include reasonably achievable goals, provide adequate online demonstration, minimize risk, and provide guidance to students through assignments and feedback (Andersson & Logofatu, 2018; Uribe, Magana, Bahk, & Shakouri, 2016).

6.2 Theme 2: Engagement and Interactions in Online Courses

Student engagement is an important component of teaching and learning regardless of the modality in which the learning occurs. However, because students and instructors in online courses do not see each other face-to-face, and because there are higher chances of online students experiencing isolation, adequate time must be spent planning strategies to engage students in online courses. Six articles were categorized under the theme of student engagement and interaction in online engineering courses. In brief, all articles underscored the importance of online student engagement and support the notion that students have better learning opportunities and experiences when they positively interact with their course content, student peers, and course instructor (Avanzato, 2017; Fatehiboroujeni, Qattawi, & Goyal, 2019; Fu, 2019; Odom et al., 2019; Schutz, Kim, & Dionne, 2018; Yousuf & Conlan, 2017). For example, Avanzato (2017) described using a virtual collaboration software tool to encourage student engagement. Students reported that the tool helped them communicate and collaborate with others while considerably increasing student-to-student and student-to-instructor interaction as compared to without the tool. In another study, visual narratives to teach online course material improved student engagement and increased interaction with the course content (Yousuf & Conlan, 2017). Finally, Odom et al. (2019) found that increased use of the course learning management system (LMS) led to improved student engagement and success as well.

6.2.1 Exemplar Studies

The exemplar studies for this theme were chosen specifically because they centered on student engagement with a focus on interactions with course content, other students, and the instructor. An exemplar of this theme is Fu (2019), who proposed a Trifecta Framework of Engagement positing that students must interact with their course content, other students, and the instructor to fully engage in the course. Fu adopted this framework in the operations management course of an online graduate engineering management degree program. Students in this course were tasked with reading materials, participating in online collaborative sessions, contributing to question-and-answer discussion boards, and completing all quizzes, exam, assignments, and a group project. In the article, Fu demonstrated that well-designed instructional videos, online sessions, threaded discussion, assignments, group projects can significantly improve student-to-content, student-to student, and student-to-instructor engagement. Students also reported that the course promoted their curiosity, critical thinking, and problem-solving skills.

In another exemplar, Fatehiboroujeni, Qattawi, and Goyal (2019) conceptualized student engagement as a function of time spent on different course activities including interaction with course content, interaction with peers, and interaction with the instructor.

They developed instruments to measure student motivation and engagement in two mechanical engineering courses and made two discoveries. First, students dedicated the most time to watching videos and assignments related to lecture and lab and devoted the least time on activities which were neither assessed nor graded, such as discussion with peers, optional problem sets, and reflection questions. Second, one-on-one student-to-student interactions (e.g., asking another student for help understanding course material, explaining course material to one or more students) were high, while student participation in the instructor-generated online discussion boards was minimal, in both courses.

6.2.2 Research Implications

Potential directions for future work include (1) analyzing how student interactions influence student learning and engagement at different points during a course, (2) determining the optimal nature and amount of student interaction with their course content, student peers, and course instructor to maximize student learning and engagement, and (3) examining how the quality and type of students' interactions in their online course enhance student learning and course completion. Further, despite the importance of student engagement in online courses, little work has provided specific measures, formulae, or frameworks for calculating online student engagement scores. One exception is Kittur et al. (2021), who computed online undergraduate engineering students' engagement scores based on their patterns of interaction with their course learning management system (LMS). More research is needed to encourage more widespread (and modification) of this technique in engineering and other disciplines.

6.2.3 Practice Implications

Instructors must intentionally create opportunities within online courses for students to interact with the course content, other students, and the instructor, as these interactions play a significant role in enhancing students' engagement, learning, and success rate (Avanzato, 2017; Fu, 2019). The studies under this theme provide several suggestions for increasing student engagement and interaction. For example, instructors can use different techniques to involve students in the course and encourage their participation, such as interaction with the faculty member, group activities, and poster sessions (Avanzato, 2017). They can increase student participation in discussion forums by assigning credit to student responses to discussion board items and providing examples that initiate discussion and sharing thoughts and ideas (Fatehiboroujeni et al., 2019). Instructors can adopt tools such as visual narratives which motivate student engagement by providing personalized information about course engagement to date, resources used, and time spent on activities (Yousuf & Conlan, 2017). Finally, they can monitor student logins to their course learning management system (LMS) to better understand their engagement – Odom et al. (2019) revealed a medium correlation between the average number of times students were expected to log into their LMS and institutional student engagement score, suggesting that requiring students to visit their LMS more often will more likely lead to increased engagement and success in the course.

6.3 Theme 3: Assessment in Online Courses

Assessment plays a critical role in evaluating student progress and performance toward the attainment of educational goals. Eight studies were classified under this theme. Some of the articles described the assignments, quizzes, midterms, final exams, online discussions, and projects used to formally assess student learning, formative assessments to support student learning, and the effectiveness of the online courses (Balagiu & Sandiuc, 2020; Chatterjee, Kamal, & Wang, 2016; Cooper et al., 2020; Danaher, 2014; Fu, 2019; Purwar & Scott, 2019). Another article detailed the instruments used to assess students' conceptual knowledge and identify potential causes for misconceptions (e.g., Pamplona, Seoane, & Bravo-Agapito, 2018). Yet another article provided an overview of best practices for assessing academic misconduct (Siddhpura & Siddhpura, 2020). They also discussed the post-course evaluation of student learning through surveys, questionnaires, and other relevant instruments (Cooper et al., 2020; Fu, 2019; Purwar & Scott, 2019).

6.3.1 Exemplar Studies

The exemplar studies for this theme were chosen to highlight the importance of assessments, and the drawbacks of poorly designed assessments, and the design and implementation of formative assessments to support learning. Designing robust assessments is important since poorly designed assessments can lead to academic misconduct because they may make it easier for students to cheat. In their review article, Siddhpura and Siddhpura (2020) analyzed various forms of academic misconduct, student motivation for involvement in academic misconduct, and ways to identify academic misconduct in online engineering. The authors argued that plagiarism and contract cheating in online assessments can be minimized using three kinds of approaches: (1) a virtues approach, in which students are encouraged not to cheat, (2) a prevention approach, in which prudent course design and delivery and effective online assessments minimize the likelihood that students can cheat, and (3) a police approach, in which students involved in academic misconduct are penalized.

In another study, Chatterjee, Kamal, and Wang (2016) illustrate the design and implementation of formative assessments to support learning in an online graduate computer engineering course. The assessments included asynchronous online discussions, virtual labs, open-ended module assignments, and a culminating project. The virtual labs provided students opportunities to interact with peers and simulate the application of course content in the form of experiments, the assignments mimicked real-life situations in which students must connect their work to problems that occur in real-life, and the final project enabled students to apply their learning from their course to propose a feasible solution to an identified problem. The instructor reflected on the course that these assessment activities together promoted student creativity and critical thinking.

6.3.2 Research Implications

Differences between the face-to-face and online learning modalities bring challenges and opportunities to explore differences in the effectiveness of their assessments. Further research in this area is required to answer questions such as how effective assessments designed for face-to-face courses are when used in the online learning format and what changes must be made (if any) in the design of assessments to facilitate the translation from the face-to-face learning format to the online learning format. Separately, there is a need to further investigate the strategies for assessing and addressing student misconceptions to enhance student learning in the online space (Pamplona, Seoane, &

Bravo-Agapito, 2018).

6.3.3 Practice Implications

Since monitoring student behavior during assessment in online courses is comparatively more difficult than in face-to-face courses, and poorly designed assessments may make it easier for students to cheat and can lead students towards academic misconduct (Siddhpura & Siddhpura, 2020), adequate attention must be given to the design of effective assessments. Creating awareness about academic integrity, establishing the instructor's role as both advisor and mentor, encouraging lifelong learning, creating awareness about the benefits and drawbacks of information available online and cautioning its use, and setting high academic integrity expectations are some strategies that instructors can use to reduce academic misconduct (Siddhpura & Siddhpura, 2020). Further, instructors should try to include different types of assessment in their online courses to evaluate student understanding of course content, just as they might in face-to-face courses. Open-ended assignments, real-world laboratory experiences, and course projects can supplement traditional assessments such as exams and quizzes to help boost students' conceptual understanding (Chatterjee, Kamal & Wang, 2016).

6.4 Theme 4: Feedback in Online Courses

Feedback supports student learning in both online and face-to-face course settings. The five articles under this theme address the importance of two types of feedback: the feedback the instructor gives to students throughout the course, and the feedback the students give to the instructor during and towards the end of the course. A few articles discuss the differential importance of instructors providing text-based, interactive, and automated feedback to students (Rutz & Ehrlich, 2016; Sancho-Vinuesa et al., 2018). Other articles talk about the importance of collecting student feedback in online courses to evaluate the course's effectiveness as well (Fu, 2019; Mansor & Ismail, 2012; Purwar & Scott, 2019).

6.4.1 Exemplar Studies

The exemplar studies in this theme were chosen to emphasize the different types of feedback used in engineering education research, specifically, text-based, interactive, and automated feedback. Rutz & Ehrlich (2016) used the Community of Inquiry (COI) framework to evaluate the use of text-based and interactive feedback on learner engagement in an online course on effectiveness in technical organizations. Learners were offered both conventional text- based feedback and interactive feedback on assignments, and surveys with five-point Likert scales and open-ended questions were used to collect student perceptions on both types of feedback and to assess the impact of these feedback formats on student perceptions related to different parts of the COI framework (cognitive presence, social presence, teacher presence). The responses showed that both formats for receiving instructor feedback helped students feel connected to the course. However, students rated their perceptions of the three elements related to the COI framework as higher for the interactive feedback than for the text-based feedback.

In another study, Sancho-Vinuesa et al. (2018) presented the use of a quiz-based assessment tool with automatic feedback in two mathematics courses for computer and telecommunications engineering students. The tool provides random self-evaluation exercises to assess student learning, such as multiple-choice, true or false, matching, and short answer questions. The results revealed that students' learning of mathematical analysis concepts, engagement, and completion rates all increased from previous semesters with the adoption of the new application.

6.4.2 Research Implications

Further research is needed into (1) the different types of feedback that can enhance student learning and performance in an online engineering course, (2) the means to assess the quality of feedback provided in an online engineering course, and (3) the impact of feedback on student learning in an online engineering course. Some potential questions tying these areas together are how students perceive automated feedback as compared to the feedback they receive from the instructor, how the quality of automated feedback compares to the feedback they receive from the instructor, and how the differences between automated and instructor feedback affect student learning (Sancho-Vinuesa et al., 2018). This question is important because students in online classes already have limited interactions with their instructors, and automating feedback results in even more of a loss in possibility to obtain personalized feedback. Separately, while collecting student feedback at the end of a course is common (Fu, 2019; Mansor & Ismail, 2012; Purwar & Scott, 2019), these types of evaluations end up focusing on course outcome attainment or student perceptions about the course. Determining strategies to effectively collect meaningful data as a part of student course evaluations represents another future research area. Course evaluations are important in refining and improving courses for future delivery; hence, collecting meaningful course evaluation data is essential.

6.4.3 Practice Implications

Instructors in the online education space are encouraged to provide students feedback to facilitate learning. Different types of feedback can be given, including text-based feedback, interactive feedback, and automated feedback (Rutz & Ehrlich, 2016; Sancho- Vinuesa et al., 2018). Instructors can try each of these different techniques of giving feedback and determine which types work best for their course, their students, and themselves. Further, instructors can collect student feedback during and near the end of the course to help them reflect on their course design and delivery and look for opportunities to make improvements to their course in subsequent offerings (Fu, 2019; Mansor & Ismail, 2012; Purwar & Scott, 2019). Hence, instructors are recommended to invest time in deciding which type of data to collect during and near the end of their course to help them better shape their courses.

6.5 Theme 5: Challenges in Online Engineering

Nine articles were categorized under the theme of challenges in delivering online engineering courses. Three out of the nine articles focused primarily on challenges in online engineering (Hachey, Wladis & Conway, 2015; Perales Jarillo et al., 2019; Pedrosa et al., 2020). Despite the numerous advantages that online education offers (Allen, Seaman, Poulin, & Straut, 2016; Seaman, Allen, & Seaman, 2018), online courses also face challenges, such as comparatively lower student sense of belongingness and higher student feelings of isolation and attrition relative to face-to-face courses (Bowers & Kumar, 2015; Gregori, Martínez, & Moyano-Fernández, 2018; Robertson, 2020; Shea & Bidjerano, 2016). These challenges cannot be ignored and need to be addressed as they negatively impact student experiences, learning, and success. In addition, several articles whose primary focus was not challenges still documented various challenges faced by online instructors, including challenges using the course learning management system (LMS), challenges designing online laboratories and design projects, challenges maintaining student engagement and student-faculty interactions, challenges equipping students with e-learning skills, challenges closing the gender gap in online engineering graduate enrollments, challenges providing timely feedback, challenges providing clear enough instruction, and technical challenges (Cooper et al., 2020; Hammout & Hosseini, 2020; Kiridena, Samaranayake, & Hastie, 2014; Levy & Ramim, 2017; Rutz & Ehrlich, 2016; Zhang, 2020).

6.5.1 Exemplar Studies

The exemplar studies for this theme were chosen because detailing challenges in online engineering was an important aspect of the article's contribution. Pedrosa and colleagues (2020) identified the pedagogical and technical challenges that arose from implementing SimProgramming in an online software development laboratory for informatics engineering students. SimProgramming is a motivation-based instructional approach intended to teach students programming through a dynamic process of design, development, testing, and analysis. The authors adapted SimProgramming to the online environment to develop students' self-regulation and co-regulation learning skills. The identified challenges included low and late student participation, student sense of isolation, inadequate feedback mechanisms, and unclear task descriptions, attributable mostly to ineffective communication between the instructor and the students. In addition, three out of 33 students dropped out of the course, citing enrollment in multiple courses and pressing job requirements as reasons.

In another study, Hachey, Wladis, and Conway (2015) investigated the impact of student performance and prior online course experiences on the successful completion of future online courses. This study used data from 1,566 community college students enrolled in online STEM courses together with logistic regression. The study revealed that students' prior online experience significantly predicted the outcome of subsequent online courses, controlling for GPA. Specifically, students who were unsuccessful in completing prior online courses and had lower GPAs were at higher risk than other students of dropping out of or failing subsequent online courses.

6.5.2 Research Implications

Pedrosa et al., (2020) reported that students struggle with feelings of isolation, low sense of belongingness, low participation, and misunderstanding of task-related descriptions in their online courses. Research is required to explore these challenges in online engineering education and the factors that influence them. Additionally, Hachey et al. (2015) found that students' previous unsuccessful experiences in online courses and low GPA can increase their likelihood of dropping from future online courses. Therefore, investigating the types of interventions and strategies that mitigate these influences represents another potential direction for future research.

6.5.3 Practice Implications

Ensuring that all course information (e.g., instructions, resources, deadlines) is clear to students is important for maintaining student interest, engagement, and retention (Pedrosa et al., 2020). Hence, instructors must devote sufficient time to examining the material offered to students and confirming that the information makes sense as intended. Further, online instructors should get to know their students and monitor their students' progress in the course for clues that they are at risk of dropping from the course (Hachey, Wladis, & Conway, 2015).

7. Intersection of Themes

While the five themes presented in the findings section are distinct, several papers included in this review look at intersections across themes. For example, Pedrosa et al. (2020) looked at the intersection of the content design and delivery and challenges in online engineering themes while examining the pedagogical and technical challenges encountered in implementing SimProgramming in an online software development laboratory. In another study, Purwar and Scott (2019) examined the integration of student feedback and assessment into the design and implementation of an online course to evaluate course effectiveness, representing work at the intersection of the content design and delivery, assessment, and feedback themes. Finally, Fu (2019)'s work sharing their experiences designing and teaching an online Operations Management course lay at the intersection of the content design and delivery, student engagement and interaction, assessment, and feedback themes, as the main goals of the study were understanding how to engage students in an online learning environment and evaluating the effectiveness of the engagement with evidence collected from the students.

Other studies could be conducted at the intersections of the themes identified in this systematic literature review, generating additional observations and implications for research and practice, as well. For example, a potential research question could be: what aspects of content design and delivery, assessment, and feedback influence engineering students' engagement and learning in their online courses, and how do engineering students perceive these different aspects as influencing their sense of belonging and persistence in their online courses? Studies could also be conducted to answer, what are some of the challenges that arise in the areas of content design and delivery, assessment, providing and receiving feedback, and engaging students in online courses, and how do these challenges affect the learning experiences and persistence decisions of students with different demographic characteristics? Additionally, examining the importance of feedback in assessing online student outcomes is another potential direction for further research.

8. Future Work

From this systematic literature review, some potential research directions emerge. First, a few articles featured frameworks with common aspects including student engagement with peers, instructors, and the course content or learning management system (LMS); however, no framework was repeated across the articles in its entirety. Thus, there is an opportunity to test and apply existing frameworks to new research in the online learning space and propose new frameworks for use in this space as well. Second, studies focused on fundamental research were more likely than those focused on course development to use advanced research methods and more likely than those focused on course and intervention development to use larger sample sizes spanning multiple courses or institutions. As our community creates knowledge around effective pedagogical practice in online engineering education, these trends suggest an opportunity to elevate studies about teaching practices to the level of larger-scale investigations. Finally, only two studies from the sampled articles focused on broadening student participation in online engineering courses; this indicates a need for more research on the experiences of traditionally underserved students (e.g., Black and Brown students, women, students with disabilities) in online engineering education.

9. Summary

In this article, thirty-nine articles related to online engineering education research were critically reviewed, which resulted in five distinct themes: content design and delivery, student engagement and interactions, assessment, feedback, and challenges in online engineering courses. Exemplar studies and implications for research and practice were summarized for each theme. Additionally, an analysis of current trends in research on online engineering education reveals (i) increasing interest in the online learning format by both researchers and practitioners with time, (ii) a center of gravity for the online engineering education research being conducted globally within the U.S., (iii) broad applicability of online learning within engineering, and (iv) a relatively large scope for creating, testing, and applying research and/or conceptual frameworks in the online engineering learning space.

CHAPTER 3

DEVELOPMENT OF A STUDENT ENGAGEMENT SCORE FOR ONLINE UNDERGRADUATE NGINEERING COURSES USING LEARNING MANAGEMENT SYSTEM INTERACTION DATA

1. Overview

While researchers agree that student engagement in online courses is a function of time dedicated to course-related activities, there is little consensus about the best way to quantify the construct. This study introduces a measure for undergraduate engineering students' engagement in online courses using their interactions with their online course learning management system (LMS). Data from 81 courses offered by three fully online, undergraduate engineering degree programs generated a total of 3,848 unique student-course combinations (approximately 2.7 million rows of LMS interaction data), to which we applied a five-step process to calculate a single score representing student LMS engagement. First, we converted the students' LMS interaction data into a set of *natural* features representing the time they spent per three-day period on various course elements, such as quizzes, assignments, discussion forums, etc., and how these times changed across the duration of the course. We then used the natural features to derive 216 *relative* features describing deviations from typical interaction patterns among students in the same course. Next, we conducted association rule mining on a training portion of the dataset to generate rules separately describing the behavior of students who completed the course (completers) and those who chose to drop early (leavers). The rules generated were applied to students from the testing portion of the dataset to compute the percentage of unique rules met by completers and leavers. Finally, the mathematical difference between the percentages of completer and leaver rules met by each student was found to be the best measure of student engagement.

2. Introduction

Online education is rapidly expanding due to its accessibility, scalability, and flexibility (Allen & Seaman, 2016; Seaman, Allen, & Seaman, 2018). One of the major challenges in online courses is student course-level attrition, which is higher in the online format than in face-to-face courses (Bowers & Kumar, 2015; Gregori, Martínez, & Moyano-Fernández, 2018; Shea & Bidjerano, 2016). Researchers have tried to address higher attrition in online courses by investigating its probable causes. For example, Hart (2012) identified motivation, onli;ne learning satisfaction, sense of belonging in the community, peer and family support, communication with the instructor, and time management skills as factors influencing students' decision to persist in online courses. Other important factors in students' successful completion of online courses have included students' prior academic achievement, previous information technology training, continuous academic enrollment, and financial assistance (Salvo, Shelton, & Welch, 2019). Researchers have also predicted online students' course persistence using data describing the students' patterns of interaction with their online course (Chatman Jr, 2020; Cohen, 2017; Henrie et al., 2018; Moreno-Marcos et al., 2020; Romero & Ventura, 2010; Watts, 2019). For example, Shelton, Hung, and Lowenthal (Shea & Bidjerano, 2016) identified students at risk of dropping their online course using student-teacher and student-

student interaction data, where the frequency of online interactions proved to better indicate student persistence and success than did the length of interactions. Aguiar et al. (2014) predicted persistence using first-year engineering students' electronic portfolios, extracting information about their course engagement through their reflections about engineering advising, project updates, and engineering exploration throughout the course. Using attributes related to student activities such as assignment skips, assessment performance, and video skips and lags to predict student dropout in online courses, Halawa et al. (2014) were able to successfully flag 40-50% of students who dropped out of the course while they were still enrolled. Finally, a study by Morris & Finnegan (2008) student attribute data and student course interaction data to predict students' course-level persistence decisions in separate studies.

Each of the studies above underscores the potential to use data related to students' activities in online courses to predict students' persistence decisions. This paper similarly presents evidence supporting the development and efficacy of a student engagement measure based on the student-LMS data interaction patterns that uniquely identify course leavers and completers in online undergraduate engineering courses. We focus on online undergraduate engineering students specifically, given the steadily increasing number of online courses and programs for undergraduate engineering students over the last decade (Kocdar, Bozkurt, & Goru Dogan, 2021; Seaman, Allen, & Seaman, 2018; Zeng et al., 2018) and the potential for greater student attrition due to the difficulties of replicating in the online formal typical aspects of the undergraduate engineering experience (Baytiyeh & Naja, 2012; Gercek, Saleem, & Steel, 2016). This work is part of a larger National Science Foundation-funded study to develop and evaluate a theoretical model for online undergraduate engineering student persistence by combining student attribute and LMS interaction data (Brunhaver et al., 2019). A summary of the literature on student engagement in online courses is provided next.

3. Student Engagement in Online Courses

Student engagement is a construct widely considered in educational research, in both face to face and online modalities, due to its demonstrated correlation with several positive student outcomes, including course level persistence (Quaye, Harper, & Pendakur, 2019; Vytasek, Patzak, & Winne, 2020). While some studies have focused on cognitive measures of student engagement such as students' motivations and strategies for learning (Richardson & Newby, 2006), others have operationalized engagement as student effort toward educationally advancing activities (Bote-Lorenzo & Gómez-Sánchez, 2017; Boyer & Veeramachaneni, 2015; Coates, 2007; Fei & Yeung, 2015) and interaction with classmates, instructors, and the courses themselves (Dixson, 2015). A growing body of work within this category uses learning analytics to track student engagement indicators such as the number of assignments completed, discussion board messages posted, quizzes taken, and emails written (Bohan & Stack, 2014; Karaksha et al., 2013; Petty & Farinde, 2013; Stewart, Stott, & Nuttall, 2011; Trumbore, 2014). For example, Bote-Lorenzo and Gómez-Sánchez (2017) calculated students' engagement scores by averaging the percentages of assignments submitted, exercises completed, and lecture videos watched through the students' course learning management system (LMS), and the change in students' engagement scores as the difference in percentages completed between consecutive units in the course. Yet more studies have correlated learning analytics-based measures of student engagement with student persistence. In one study, Balakrishnan and Coetzee (2013) used student's interactions with their Massive Open Online Courses (MOOCs) to predict their retention in the MOOC. In another study, Kizilcec, Piech, and Schneider (2013) used students' patterns of interactions with their course LMS to predict students' engagement type (i.e., completing, auditing, sampling, or disengaging from the course) which they proposed educators could use as a warning system to identify students at risk of dropping the course.

The amount of time spent on LMS activities can help understand student engagement in online courses, and time can be studied using either natural or relative reference frames. The natural reference frame refers to an individual's time spent on LMS-related activities and the change in individual's time spent on LMS-related activities over a certain period, and the relative reference frame refers to the individual's time spent on LMS-related activities as compared with their classmates (Vytasek, Patzak, & Winne, 2020; Wise et al., 2016). Few studies (Humber, 2018; Sneed, 2019; Young & Bruce, 2011) consider how student engagement varies over time and relative to one's peers, despite evidence that student engagement is a function of course norms (Coates, 2007). Researchers lack a measure of online student engagement they can confidently utilize in their work that captures the relative reference frames.

This paper provides full details supporting our methodology to create a numerical value describing the construct of student engagement in online undergraduate engineering education. We begin addressing this goal by exploring how LMS interaction data can be used to compute student engagement scores within online undergraduate engineering courses. The following sections fully document our data set and methodology used to create a numerical value describing this construct. Our analysis offers researchers in the educational data mining space a novel approach to conduct their own investigations related to online student engagement, an important construct to studying student persistence in online courses.

4. Dataset

The dataset for this study comes from 81 courses offered by three fully online, ABET-accredited undergraduate engineering degree programs at a large, public, southwestern university between Fall 2018 and Spring 2020. Nine courses were from electrical engineering, 35 were from engineering management, and 37 were from software engineering. All courses were 7.5 weeks in duration and used Canvas as the learning management system (LMS) platform. We collected approximately 2.7 million rows of LMS interaction data from 3,848 unique student-course combinations. Unique student-course combinations were considered since students could be enrolled in more than one course. About 90% of student-course combinations came from students who persisted in the course to its completion. Table 10 summarizes the dataset in terms of the number of courses from each program and the number of persisting and non-persisting students for each 7.5-week period of data collection. Table 11 summarizes the student enrollment data across three-degree programs based on the different course levels: introductory (100 level courses), intermediate (200 level courses), advanced-intermediate (300 level courses), and advanced (400 level courses). Approximately, 17% of the total courses belong to the introductory, 30% to the intermediate, 34% to the advanced-intermediate, and 19% to advanced level courses.

Table 10. Student Enrollment Data Across Different Sessions

#	Session	Number of Courses			Persisting students	Non-persisting students
		Electrical engineering	Engineering management	Software engineering		
1	Fall-B 2018	1	3	0	156	17
2	Spring-A 2019	1	5	8	611	56
3	Spring-B 2019	1	6	7	581	82
4	Fall-A 2019	2	8	7	727	83
5	Fall-B 2019	3	5	6	675	79
6	Spring 2020	1	8	9	717	64

Table 11. Student Enrollment Data Based on Course Levels Across Degree Programs

Degree program	Course level			
	Introductory	Intermediate	Advanced-intermediate	Advanced
Electrical Engineering	663	288	-	-
Engineering Management	-	-	509	407
Software Engineering	-	883	775	323

Each row of LMS data represents a different student interaction with their course LMS, whether navigating to a particular type of page by clicking on a link (such as to quizzes, assignments, discussion forums, modules, wiki pages, attachments, grades, the syllabus, or announcements) or submitting quizzes and assignments. Table 12 describes each activity type considered in this study. Table 13 illustrates the raw structure of the dataset with de-identified student IDs and course IDs, this table has been reproduced from the previously published work (Kittur, Bekki, & Brunhaver, 2020). The raw data includes the following elements: student ID (student_id), course ID (course_id), time of the event (eventtime), type of the event (eventtype), action related to an event (Action), activity type (object_name) and student enrolment status in the course (enrl_status).

Table 12. Description of the Activity Types

#	Activity Type	Description
1	Quizzes	Student submitting a quiz, student navigating to a quiz
2	Assignments	Student submitting an assignment, student modifying an assignment, student navigating to an assignment
3	Discussion forum	Student posting a message, student navigating to a discussion thread
4	Wiki pages	Student navigating to a wiki page
5	Attachments	Student navigating to an attachment
6	Modules	Student navigating to modules
7	Syllabus	Student navigating to syllabus
8	Grades	Student navigating to grades
9	Announcements	Student navigating to announcements

Table 13. Structure of the Raw Data

eventtime	student_id	course_id	eventtype	Action	object_name	enrl_status†
10/10/2018 9:21:33	A	2018 FallB	NavigationEvent	NavigatedTo	quizzes:quiz	ENRL
10/15/2018 9:22:18	A	2018 FallB	NavigationEvent	NavigatedTo	Attachment	ENRL
10/11/2018 19:54:17	B	2018 FallB	NavigationEvent	NavigatedTo	Syllabus	ENRL
10/16/2018 15:55:03	B	2018 FallB	AssessmentEvent	Submitted	-	ENRL
10/22/2018 10:06:53	C	2018 FallB	NavigationEvent	NavigatedTo	Modules	ENRL
10/22/2018 17:11:47	C	2018 FallB	NavigationEvent	NavigatedTo	Grades	ENRL
10/13/2018 23:05:59	D	2018 FallB	AssignableEvent	Submitted	-	WDRW
10/16/2018 23:45:24	E	2018 FallB	Event	Modified	-	WDRW
10/24/2018 0:00:55	F	2018 FallB	NavigationEvent	NavigatedTo	announcements	WDRW

†ENRL = student remained enrolled in the course; WDRW = student withdrew from the course

5. Procedure and Results

5.1 Feature Creation

The graphical representation of the process used in preparing the data by creating and selecting features required to conduct association rule mining (ARM) analysis is described in Figure 4 and explained in detail in this section. We used the students' LMS interaction data to create 2,161 natural features for each unique student-course combination. The natural features represent one of two categories of activity. First, they represent a student’s time spent on LMS-related activities and include time spent on quizzes, assignments, discussion forums, wiki pages, attachments, modules, the syllabus, grades, announcements, and the LMS overall. Second, natural features also represent the raw number of quiz and assignment submissions by a student. Each natural feature was calculated over consecutive three-day windows; for example, "time spent on quizzes" was calculated across each three-day period in the course (i.e., days 1-3, days 4-6, etc.) The length of three days, also referred to as the “analysis window length”, or just “window length” was selected because it allowed us to detect the students’ LMS temporal patterns as students may choose different times and days to work on the different tasks in the course. The three days data will be sufficient to analyze students’ temporal patterns as considering more than three days as an analysis window period in a 7.5-week course could gloss over important details. The first analysis window for each course was eliminated because it corresponded with the university’s semesterly course drop deadline (i.e., students can drop the class during the first three days without penalty). After removing this first analysis window of data, 16 analysis windows of data for each course remained. Table 14 shows how the sample data were structured (Kittur, Bekki, & Brunhaver, 2020). The columns represent the student's time spent on quiz (tquiz), assignment (tassignment), discussion forum (tdforum), wiki pages (twiki), attachments (tattach), modules (tmodules), course syllabus (tsyllabus), course grades (tgrades), and student's course status in a given analysis window.

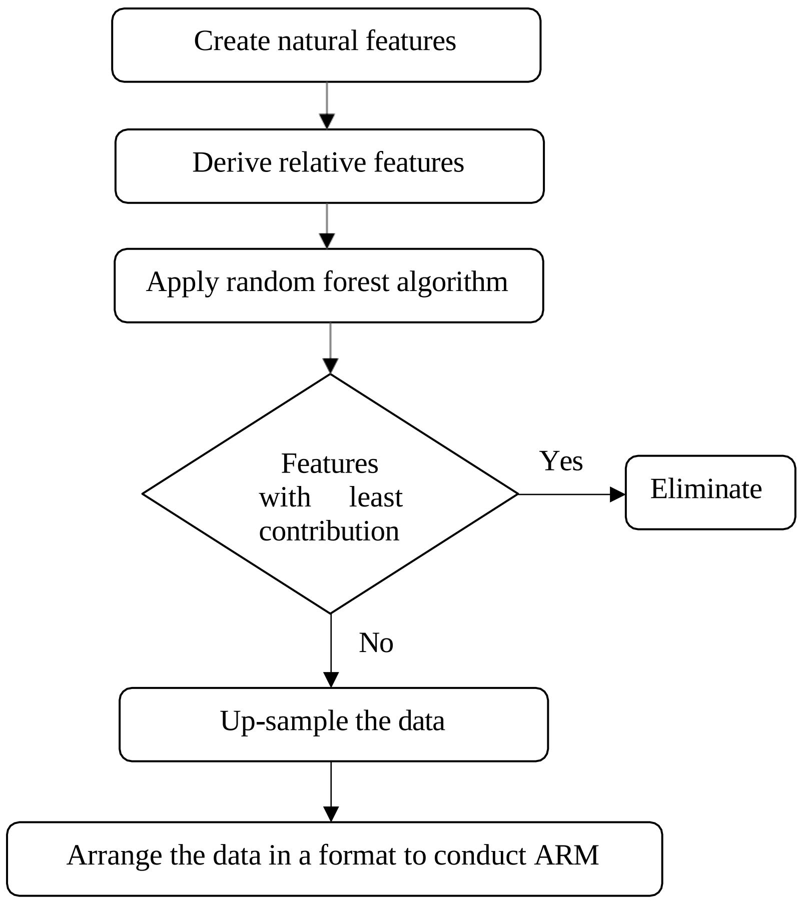

Figure 3. Preparation of Data Required to Conduct ARM

Table 14. Structure of the Data with Sample Natural Features in a Particular Analysis Period

Student_id	tquiz	tassignment	tdforum	twiki	tattach	tmodules	tsyllabus	tgrades	Status†
A	57.36	0.422	0.383	278.5	193.1	111.9	4.31	3.80	ENRL
B	15.01	0.266	0.000	30.00	54.43	0.000	0.46	0.00	ENRL
C	18.81	0.100	2.450	239.7	291.1	138.2	0.01	0.18	ENRL
D	9.960	0.160	1.580	0.000	91.13	0.760	0.01	0.55	ENRL
E	48.68	0.850	1.010	184.8	32.03	1.410	0.00	0.52	ENRL
F	93.00	0.000	0.230	5.580	27.88	90.08	2.36	0.00	ENRL
G	9.580	4.130	0.570	92.50	88.91	61.75	3.35	0.28	WDRW
H	2.730	0.100	0.060	1.460	6.500	0.230	2.30	0.00	WDRW
I	109.8	0.420	0.570	227.8	16.95	183.1	0.00	0.52	WDRW
J	0.000	0.000	2.130	0.030	94.60	1.210	0.01	0.00	WDRW

†ENRL = student remained enrolled in the course; WDRW = student withdrew from the course

The broader aim of this study was to develop a numerical representation of student engagement, which is known to be a function of course norms (Coates, 2007). Correspondingly, from the natural features, relative features, which compare LMS interaction activities of each student to the "norms" for others in their same course, were calculated. Table 15 lists all the relative features utilized in the study and includes, for example, a feature describing the difference between an individual student's time spent and the average time spent for all students in the class during the analysis windows. In total 216 relative features describing change over time and deviations from typical LMS- interaction patterns among students in the same course, were generated. Of note is that these features, shown in Table 15, are not temporal features capturing the change in an individual student's behavior over time, but features that describe difference between an individual student's activities and those of the "norms" within the class.

Table 15: Relative Features Notation and Representation

Feature #	Feature description and mathematical representation
	Notations: n_{jk} – Number of students in course *j* in analysis period *k* M_{ijk} – Number of submissions by student *i* in course *j* in analysis period *k* G_{ijk} – Time spent or number of submissions by student *i* in course *j* in analysis period *k*. D_{ij} – Duration of the course considered for a student *i* and course *j* *N* – number of windows
F1	Difference between an individual student's time spent and the average time spent for all students in the class, in a particular analysis period $$G_{ijk} - \frac{\sum_{i \in n_{jk}} G_{ijk}}{n_{jk}} \quad \forall\, k \in D_{ij}$$
F2	Difference between an individual student's change in time spent and the average change in time spent for all students in the class, in a particular analysis period $$\left(G_{ijk} - G_{ijk'}\right) - \left[\frac{\sum_{i \in n_{jk}} (G_{ijk} - G_{ijk'})}{n_{jk}}\right]$$ $$\forall\, k, k' \in D_{ij} \; and \; k < k'$$
F3	Difference between the maximum change in time spent for all students in the class and an individual student's change in time spent, in a particular analysis period $$max_{i \in j}(G_{ijk} - G_{ijk'}) - (G_{ijk} - G_{ijk'})$$ $$\forall\, k, k' \in D_{ij} \; and \; k < k'$$
F4	Difference between an individual student's change in time spent and the minimum change in time spent for all students in the class, in a particular analysis period $$(G_{ijk} - G_{ijk'}) - min_{i \in j}(G_{ijk} - G_{ijk'})$$ $$\forall\, k, k' \in D_{ij} \; and \; k < k'$$
F5	Difference between the maximum time spent by a student in the class and the time spent by an individual student, in a particular analysis period $$max_{i \in j,k}(G_{ijk}) - G_{ijk} \quad \forall\, i \in j, k \; and \; k \in D_{ij}$$
F6	Difference between the time spent by an individual student and the minimum time spent by a student in the class, in a particular analysis period $$G_{ijk} - min_{i \in j}(G_{ijk}) \quad \forall\, i \in j, k \; and \; k \in D_{ij}$$
F7	Difference between the variance of an individual student's time spent and the average variance of time spent for all students in the class across three different windows $$\frac{1}{N-1}\sum_{k=1}^{N}\left[G_{ijk} - \frac{\sum_{i=1}^{n_{jk}} G_{ijk}}{n_{jk}}\right]^2 - \frac{\frac{1}{N-1}\sum_{k=1}^{N}\left[G_{ijk} - \frac{\sum_{i=1}^{n_{jk}} G_{ijk}}{n_{jk}}\right]^2}{n_{jk}}$$ $$\forall\, i \in j, k \; and \; N \in (3 \; to \; 15) \; and \; k \in D_{ij}$$

F8	Difference between the variance of time spent by an individual student and the minimum variance of the time spent by a student in the class across different windows. $$\frac{1}{N-1}\sum_{k=1}^{N}\left[G_{ijk}-\frac{\sum_{i=1}^{n_{jk}}G_{ijk}}{n_{jk}}\right]^2-min\left\{\frac{1}{N-1}\sum_{k=1}^{N}\left[G_{ijk}-\frac{\sum_{i=1}^{n_{jk}}G_{ijk}}{n_{jk}}\right]^2\right\}$$ $$\forall\ i\in j,k\ and\ N\in(3\ to\ 15)\ and\ k\in D_{ij}$$

Calculating the relative features required specifying the number of analysis windows over which each relative feature would be calculated and selecting which particular analysis windows during the duration of data collection would serve as the basis of their calculation. This is an important step to meet our analysis window as we do not wish to include students who have not spent enough time and dropped from the course. Given the fact that, the total percentage of course leavers were so small in comparison with the course completers, we were careful in selecting the length of the analysis window such that it captures the students' relevant behavior and to not lose a greater number of dropping students from our dataset. We arranged the percentage of dropped students considering multiple analysis window lengths and we decided to use three analysis windows data. We chose to calculate relative features based on three consecutive analysis windows (e.g., analysis windows 1-3, analysis windows 2-4, analysis windows 3-5, etc.) because it was the minimum number necessary to calculate our variance-related relative features (see Table 16) while still yielding the maximum number of students who dropped in our dataset during each analysis period, which was helpful in discriminating between the behavior of course leavers from that of course completers.

To discriminate the behavior of course completers and leavers, it is important to determine which analysis windows to be considered such that the relevant data is available for the analysis. We also assumed that while the features for persisting students would be nondistinctive for any analysis period during the course, the period just before a student drops would include the most distinctive feature across the duration of the course for leavers. We thus used the last three analysis windows before a student's withdrawal from the course as the analysis period for leavers and randomly selected three consecutive analysis windows for course completers to create the relative features (Kittur, Bekki, & Brunhaver, 2020).

5.2 Feature Selection

Once the relative features were developed, we used the feature selection part of the random forest algorithm (Tan, Steinbach, & Kumar, 2016) to identify features that uniquely distinguish course completers from course leavers. We randomly divided into two datasets of 31 courses (Dataset 1) and 32 courses (Dataset 2), to verify the stability of selected features. Each set of features was arranged in descending order according to their random forest Gini index, the higher of which signifies greater importance of a feature in distinguishing course completers from course leavers relative to other features. Table 16 shows the top thirty features selected using the feature selection process from each dataset, grouped based on their associated LMS-interaction activity type (e.g., quiz submission, time spent looking at grades, etc.) For example, features related to quiz submissions appeared six times in the top thirty features selected from Dataset 1 and five times in the top thirty features selected from Dataset 2. The purpose of selecting top features was to understand which relative features related to the different LMS-activity types are relatively more important in distinguishing course completers from course leavers. Relative features related to the syllabus, discussion forums, and announcements did not appear in the top thirty features selected for either dataset, and were removed from further analysis, reducing the number of relative features to 162. Readers are directed to (Kittur, Bekki, & Brunhaver, 2020) for more details on the creation of the natural and relative features.

Table 16. Frequency of Top 30 Relative Features According to LMS-Interaction Activity Type

#	**Frequency of top 30 features**	
	Dataset 1 (31 courses)	**Dataset 2 (32 courses)**
1	Quiz submission – 6	Quiz submission – 5
2	Grades – 3	Grades – 3
3	Wiki – 4	Wiki – 2
4	Canvas – 5	Canvas – 3
5	Attachment – 5	Attachment – 5
6	Quiz – 5	Quiz – 2
7	Assignment submission – 2	Assignment submission – 3
8	Assignment – 0	Assignment – 4
9	Modules – 0	Modules – 3
10	Syllabus – 0	Syllabus – 0
11	Discussion forums – 0	Discussion forums – 0
12	Announcements – 0	Announcements – 0

5.3 Association Rule Mining

The process used in conducting association rule mining (ARM) analysis is graphically presented in Figure 4 and more details about this process is described in this section. With the final 162 relative features, association rule mining (ARM) was used to generate rules uniquely describing completers and leavers. ARM discovers hidden relationships among variables in large datasets using association rules a$\rightarrow$b, where ‘a’ is the antecedent of the rule, 'b' is the consequent (Agrawal et al., 1996; Lakshmi & Prasad, 2014; Stewart, Stott, & Nuttall, 2011). The rule a➔b indicates the likelihood that a specific student's activity containing relative features in 'a' will tend to include the student's persistence decision (yes/no) in 'b.' In this study, N refers to the set of total students with unique identifiers {ID_1, ID_2, ID_3, …, ID_N}, 'a' refers to the set of Z relative features {F_1, F_2, F_3, …., F_Z}, and 'b' refers to students' decision to persist ("1") or not persist ("0") in their online course. Table 18 illustrates the format required for data to run in ARM, where rows represent transactions (students) and columns represent the itemset 'a + b' (relative features and persistence) (Agrawal, Imieliński, & Swami, 1993; Agrawal & Srikant, 1994). For example, the first row identifies a student with student ID-1 who persisted the course (Persistence=1), with low engagement rating (1) on relative features F_1 and F_z, high engagement rating (3) on relative features F_2 and F_3.

ARM requires the discretization of continuous data, which the relative features describing student engagement in our dataset were. Approaches to discretize data for use in ARM include dichotomizing values based on whether it is above or below a certain threshold, dividing data into equal sized bins, and using quartiles to assign data to different categories (Azarnoush et al., 2013; Balakrishnan & Coetzee, 2013; Mohamad, Ahmad, & Sulaiman, 2017; Taylor, 2014). We divided the data for each relative feature, Fi, into three bins before initiating ARM. The first bin had data points less than or equal to the first quartile (Q1), which were assigned a value of "low engagement" (LOW) relative to the average student in the course. The second bin had data points greater than the first quartile

(Q1) and less than or equal to the third quartile (Q3), which were assigned a value of "medium engagement" (MED) relative to the average student in the course. The last and third bin had data points greater than the third quartile (Q3), which were assigned a value of "high engagement" (HIGH) relative to the average student in the class.

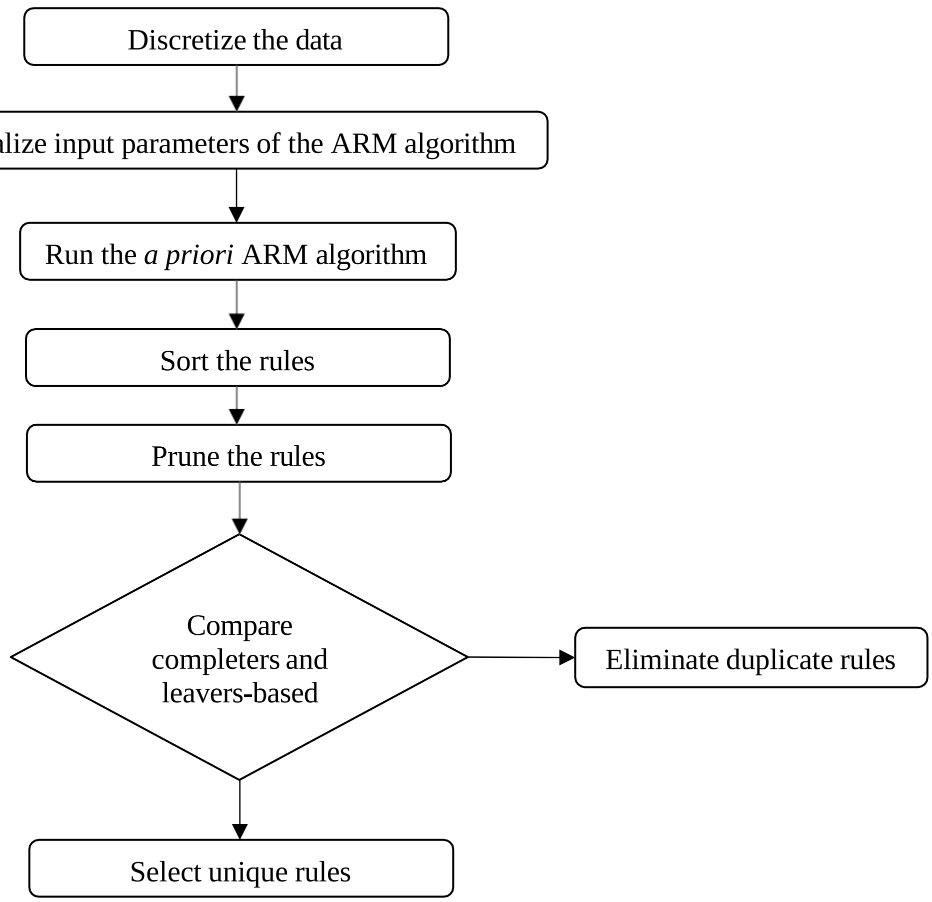

Figure 4. Association Rule Mining Process

In Table 17, 1=LOW, 2=MED, and 3=HIGH. For the third (F3) and fifth (F5) relative features (features related to the difference between an individual student and the student with maximum time/number of submissions in the class), the interpretation is slightly different from the other relative features. For features F3 and F5, a value LOW represents that a student's engagement was relatively more than that of a student with value HIGH for feature types. This is because if the difference between a student's score and the maximum score in class is smaller, it implies that the student's score was nearer to the maximum score in the class than if the difference was greater.

Table 17. Association Rule Mining Final Problem Representation

Student ID	F_1	F_2	F_3	**…**	F_Z	***Persistence***
1	1	3	3	…	1	1
2	1	2	1	…	2	0
3	3	2	2	…	3	1
…	…	…	…	…	…	…
N	2	3	1	…	2	1

Once generated, the association rules for this study were mined using the *apriori* algorithm of the *arules* package in the statistical software R (Team, 2013). First, we split the discretized data into a training dataset (80%) and a testing dataset (20%) and conducted ARM on the training dataset to generate rules capturing the behavior of course completers and course leavers, separately. A syntactic constraint restricts the items that appear in a rule (Tan, Steinbach, & Kumar, 2016), such as to understand how restricting items in the consequent affects the set of items in the antecedent, or vice versa. Syntactic constraints were placed on the consequent of each rule, as we were interested in identifying unique rules for students who persisted and students who dropped the course, respectively. We generated the rules for course completers by fixing the syntactic constraint on the consequent to "1," which looked like {set of relative features} → {persistence=HIGH}, and the rules for course leavers by fixing the syntactic constraint on the consequent to "0," which appeared as {set of relative features} → {persistence=LOW}. In addition, because choosing to include only one or two relative features in the antecedent would generate a very large number of rules, and including more than five relative features in the antecedent would generate very few rules, the minimum number of relative features allowable in the antecedent per rule was fixed to three and the maximum number of antecedents were allowed to be four, which produced an amount of variability in the rules deemed acceptable by the research team (not too many and not too few). Thus, an example rule for course completers could be that 30% of students who had a medium (=2) engagement score on relative features F1, F2, and F7 were likely to persist in the course, while an example rule for course leavers could be that 50% of students who had a medium (=2) engagement score on relative features F4 and F5, and low (=1) engagement score on relative features F6 were likely to drop the course.

To determine the optimal number of rules to generate, we tested between 20 and 70 rules in increasing increments of five by varying the rules' support and confidence values on which the number of rules ARM generates also depends. We stopped generating rules at 70, as the number of unique rules generated for course completers and course leavers approached saturation as we reached 70 rules, which became the upper bound for the number of rules tested. In other words, generating 80 or 90 rules or even higher number of rules resulted in unique rules lesser than those obtained from the 70 generated rules. The support of a rule measures how frequently the itemset appears in the dataset among all generated rules, and the confidence of a rule measures its accuracy, i.e., how often the rule is found to be true among the data (Agrawal, Imieliński, & Swami, 1993; Seaman, Allen, & Seaman, 2018). The range for both support and confidence are between 0 and 1 (or 0% and 100%), and a minimum of 10% threshold is recommended for support values (Agrawal, Imieliński, & Swami, 1993; Azarnoush et al., 2013). Higher support and confidence values in the algorithm decrease the total number of rules generated. The output confidence values in this study were always 100% because the generated rules were unique to completers or leavers only.

The total number of generated rules, rules after pruning, and unique rules for each case of the desired number of rules are presented in Table 18, along with their respective support values. The generated rules included duplicate rules and rules that were subsets of others. The rules were pruned to remove redundancies as they could introduce bias in the analysis. The rules unique to completers and leavers were determined manually using Microsoft Excel and the duplicate rules were removed. We decided to use all the unique rules in our next step in calculating student engagement. The support values to be entered in the ARM algorithm ranged from 36.2% (for 70 rules) to 39.6% (for 20 rules) for completer-based rules, and 47.4% (for 70 rules) and 51% (for 20 rules) for leaver-based rules. The input confidence values for each case of the desired number of rules ranged from 70% to 95%, these confidence values were manually adjusted to acquire the rules from 20 to 70. Generating 70 rules for both completers and leavers yielded the largest numbers of unique completer-based rules (48) and leaver-based rules (38), respectively. Hence, we chose 70 rules moving forward with the analysis. Appendix C and D show the completer-based unique rules and leaver-based unique rules.

In this study, all the unique rules were used in computing the student engagement scores. However, we note that some ARM researchers select the most important rules using the lift criterion, the ratio of a rule's confidence and support values and a standard measure for ARM (Seaman, Allen, & Seaman, 2018; Tan, Steinbach, & Kumar, 2016). A large lift value is strong indication that a rule is important and reflects a true connection between consequent and antecedent (Tan, Steinbach, & Kumar, 2016). In this study, we did not use lift to select rules as the lift values for all the rules was 1 (100%) implying that all the rules were important.

Table 18. Summary of Desired, Generated, Pruned and Unique Completer-Based and Leaver-Based Rules

#	Desired number of rules	Completers				Leavers			
		Support (%)	**Generated rules**	**Pruned rules**	**Unique rules**	**Support (%)**	**Generated rules**	**Pruned rules**	**Unique rules**
1	20	39.6	20	20	12	51.0	19	18	10
2	25	38.8	26	26	17	50.9	25	23	14
3	30	38.5	30	28	17	50.0	31	28	17
4	35	38.0	37	35	24	49.4	36	32	21
5	40	37.8	39	37	25	49.0	41	36	24
6	45	37.7	45	42	30	48.5	48	42	30
7	50	37.2	50	47	35	48.5	48	42	30
8	55	36.9	55	51	38	48.0	55	46	33
9	60	36.7	60	55	40	47.5	61	50	35
10	65	36.5	65	59	43	47.4	69	53	37
11	70	36.2	71	65	48	47.4	69	55	38

An example completer-based rule and leaver-based rule generated using the association rule mining process is shown below. These rules were randomly selected (i.e., there was no specific reason or rationale for choosing them). Readers are directed to Table 6 when reading the explanation of the rules below, as this will help better understand and appreciate the definition of the different rules generated in this study.

The following is a completer-based rule:

{*F3_quiz.sub2_3=MED*, *F4_quiz.sub1_2=MED*, *F5_quiz.sub2=MED*} →

{*Persistence=Yes*}, where,

- *F3_quiz.sub2_3* represents the difference between the maximum change in the number of quiz submissions for all students in the class and an individual student's change in the number of quiz submissions, across analysis windows 2 and 3,

- *F4_quiz.sub1_2* represents the difference between an individual student's change in the number of quiz submissions and the minimum change in the number of quiz submissions for all students in the class, across analysis windows 1 and 2, and
- *F5_quiz.sub2* represents the difference between the maximum number of quiz submissions by a student in the class and the number of quiz submissions by an individual student, during analysis window 2.

This rule had a support of 37.4%, which means that the relative features *F3_quiz.sub2_3=MED*, *F4_quiz.sub1_2=MED*, and *F5_quiz.sub2=MED* appeared together in the dataset 37.4% times. All three relative features in this rule had medium levels of student engagement relative to the average student in the course. In other words, medium levels of student engagement relative to the average student in the course on the activities related to quiz submissions are indicative of a student persisting in an online undergraduate engineering course.

Next is a leaver-based rule:

{*F6_quiz3=LOW, F6_wiki3=LOW, F6_assignment.sub3=LOW*} → {*Persistence=No*},

where,

- *F6_quiz3* represents the difference between the time spent on quizzes by an individual student and the minimum time spent on quizzes by a student in the class, during analysis window 3,
- *F6_wiki3* represents the difference between the time spent on wiki pages by an individual student and the minimum time spent on wiki pages by a student in the class, during analysis window 3, and

- *F6_assignment.sub3* represents the difference between the number of assignment submissions by an individual student and the minimum number of assignment submissions by a student in the class, during analysis window 3.

This rule had a support of 47.4%, which means that the relative features *F6_quiz3=LOW*, *F6_wiki3=LOW*, and *F6_assignment.sub3=LOW* appeared together in the dataset 47.4% times. All three relative features in this rule had low levels of student engagement relative to the average student in the course. This is to say, the low levels of student engagement relative to the average student in the course on activities related to quizzes, wiki pages, and assignment submissions are indicative of a student not persisting in an online undergraduate engineering course.

5.4 Engagement Score Determination

The process used in computing student engagement score using the rules generated by ARM is shown in Figure 5 and more details follow in this section. Using the final set of association rules for leavers and completers, we evaluated eight different candidate student engagement scores, shown in Table 19. The scores were calculated for each student in the testing dataset based on the percentage of unique completer-based rules met (X), and the percentage of unique leaver-based rules met (Y).

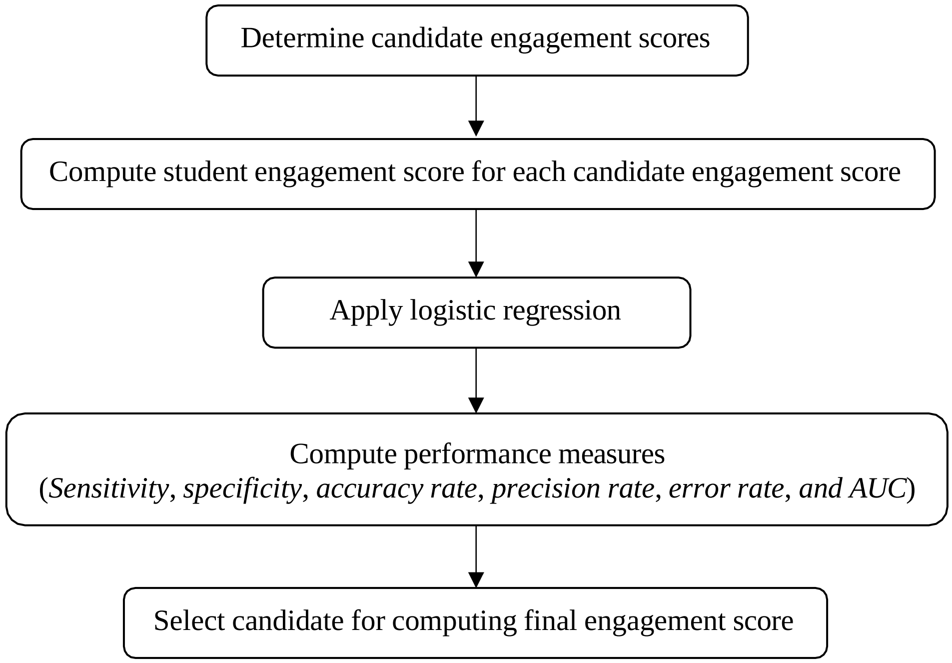

Figure 5. Computing Student Engagement Score using the Rules

Table 19. Different Candidate Student Engagement Scores

#	**Candidate student engagement scores**
1	$X - Y$
2	$\frac{X}{(X+Y)}$
3	$\sqrt{X^2 + Y^2}$
4	$\frac{1}{X} + \frac{1}{Y}$
5	$\frac{1}{Y} - \frac{1}{X}$
6	$\log(X) - \log(Y)$
7	$\log(X) + \log(Y)$
8	$\frac{\log(X)}{\log(X) + log(Y)}$

Logistic regression was then used to evaluate the efficacy of each candidate student engagement score in predicting students' online course-level persistence. A different candidate engagement score served as the predictor variable in each model, and the dependent variable across all models was persistence, with values 0=leavers and 1=completers. Notably, we needed to up-sample the data before conducting these analyses to correct the imbalance between course completers and course leavers in the dataset (Chawla et al., 2002; Rahim et al., 2019). There were approximately 12 times as many course completers as there were course leavers in this study. Such a large majority class (one ten times or larger than the minority class) can introduce bias into logistic regression analysis, which can, in turn, affect the precision and accuracy of predictions about the minority class (Lakshmi & Prasad, 2014; Rahim et al., 2019). This imbalance was handled in the statistical software R (Team, 2013) using the Synthetic Minority Over-sampling Technique (SMOTE), which uses either up- or down-sampling methods to balance unevenly distributed datasets, depending on majority or minority class (Chawla et al., 2002). SMOTE was used in this study to up-sample the minority class in the dataset, the course leavers, by creating synthetic cases (Chawla et al., 2002).

We used eight different SMOTE ratios ranging between 1:1.1 and 1:9, being within the boundaries associated with the actual ratio of leavers to completers (1:12) in the dataset, to analyze the stability of each candidate engagement score. In other words, logistic regression was applied to the data for each of eight sampling ratios of leavers to completers and for each candidate engagement score as a predictor of persistence, for a total of 64 models. We favored for the final score those whose effectiveness in predicting course-level persistence remained high. Six performance measures were considered to evaluate the goodness of each engagement score in predicting students' course-level persistence: sensitivity (the proportion of true positives predicted as such), specificity (the detection of true negatives predicted as such), accuracy (the rate of total correct predictions), precision (the rate of correct positive predictions), error rate (the rate of total incorrect predictions), and AUC (area under the ROC curve, which signifies how well the model distinguishes between two classes) (James, Witten, Hastie, & Tibshirani, 2013). Except error rate, high values on the other performance metrics indicates greater effectiveness of engagement score. Table 20 presents the output of these analyses, with the rows representing the eight different candidate engagement scores and the columns, the eight sampling ratios. Notably, every candidate measure of student engagement consistently predicted student persistence to a statistically significant level ($p<0.05$) except [inv(X)+inv(Y)] and [inv(Y)-inv(X)].

Table 20. Logistic Regression Output

Measures of Engagement	**Logistic regression coefficients**							
	1:1.1	**1:2**	**1:3**	**1:4**	**1:5**	**1:6**	**1:7**	**1:9**
[X-Y]	0.04*	0.04*	0.04*	0.04*	0.04*	0.03*	0.04*	0.04*
[X/(X+Y)]	3.58*	3.40*	4.17*	3.48*	3.55*	3.37*	3.55*	3.43*
[sqrt(X^2+Y^2)]	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*
[inv(X)+inv(Y)]	-0.45	-0.69*	-0.75	-0.57	-0.89*	-0.56	-0.63	-0.43
[inv(Y)-inv(X)]	-0.05	-0.01	0.68	0.83	0.12	0.71	0.31	0.71
[log(X)-log(Y)]	1.83*	1.75*	1.95*	1.67*	1.79*	1.63*	1.76*	1.69*
[log(X)+log(Y)]	-0.37*	-0.38*	-0.32*	-0.32*	-0.31*	-0.34*	-0.35*	-0.29*
[log(X)/(log(X) +log(Y))]	4.88*	3.03*	5.08*	3.65*	3.06*	3.39*	3.56*	3.32*

Note. Dependent variable – persistence (0=leavers, 1=completers)
*$p<0.05$

When a sampling ratio of 1:1.1 was used, most performance metrics (specificity, accuracy rate, and precision rate) were highest for the engagement score [log(X)/(log(X)+log(Y))]. When a sampling ratio of 1:3 was used, the highest performance metric in each category was distributed randomly across the eight candidate engagement scores, not suggesting any engagement score to be better than the other. However, for the remaining sampling ratios (1:2, 1:4, 1:5, 1:6, 1:7 and 1:9), most of the performance metrics were highest for the engagement score [X-Y]. The performance measures for the engagement score [X-Y] for the different sampling ratios of leavers to completers is shown in Table 21. The error rate for [X-Y] decreased as the sampling ratio increased from 1:1.1 to 1:9. Every other performance metric except specificity and AUC (fluctuates up and down as sampling ratio increases) increased with increasing sampling ratio from 1:1.1 to 1:9. Specificity which is the accuracy with which true leavers are predicted as such decreases in value is acceptable as sampling ratio increases from 1:1.1 to 1:9 because the number of leavers in comparison with the completers decrease. Hence, we selected the candidate [X-Y] for calculating the final student engagement score.

Table 21. Performance Measures for the Engagement Score [X-Y]

Performance Measures	**1:1.1**	**1:2**	**1:3**	**1:4**	**1:5**	**1:6**	**1:7**	**1:9**
Sensitivity	68.12	90.14	93.39	95.44	97.14	97.95	98.75	99.38
Specificity	62.77	42.86	27.38	22.22	19.84	13.10	13.89	13.10
Accuracy Rate	65.56	74.38	76.88	80.79	84.26	85.83	88.14	90.75
Precision Rate	66.62	75.93	79.42	83.07	85.83	87.12	88.92	91.14
Error Rate	34.44	25.62	23.12	19.21	15.74	14.17	11.86	9.25
AUC	70.2	78.7	79.6	78.5	78.8	77.5	79.1	78.3

5.5 Engagement Score Computation Process

Appendix E summarizes the step-by-step approach used in computing the final engagement score. Three sub-processes are outlined: preparing the data required to conduct association rule mining (ARM), conducting ARM, and computing the LMS engagement score using the completer- and leaver-based rules.

6. Discussion and Interpretation

In this study, a measure for undergraduate engineering students' engagement in online courses based on data describing their interactions with an online course learning management system was introduced. The results from this study suggest that the best engagement score was found to be the mathematical difference between the percentages of unique completer-based rules and leaver-based rules met by each student.

Out of 162 possible relative features, the final set of unique completer-based rules included 29, and the unique leaver-based rules included 19 relative features. The frequency with which these 29 and 19 relative features occurred among the completer- and leaver-based rules is shown in Table 22. The signifier for each relative feature includes its feature type, course activity type, and corresponding analysis windows. For example, relative feature '*F1_quiz.sub3=MED*' (#10 under the completer-based rules) represents the difference between an individual student's number of quiz submissions and the average number of quiz submissions by all students in the class during the last analysis window (analysis window 3) in the last three analysis windows selected for leavers and the random three analysis windows selected for completers. (Refer to Table 15 for details related to the numbering and types of relative features). As described previously, the discretization of the data resulted in three levels of student engagement relative to the average student in the course (i.e., 1=LOW, 2=MED, 3=HIGH), and the same can be seen in Table 12. Returning to '*F1_quiz.sub3=MED,*' this rule refers to the difference between an individual student's number of quiz submissions and the average number of quiz submissions by all students in the class during analysis window 3 as being in the 'MED' levels of student engagement relative to other students. Overall, most of the relative features that appeared in the final set of unique completer-based rules included the combinations of 'LOW' and 'MED' levels of student engagement relative to the average student in the course. In the final set of unique leaver-based rules, the relative features that most appeared included 'LOW' levels of student engagement relative to the average student in the course, except for few rules including relative features with 'LOW' and 'MED' levels of student engagement. This makes sense as students who leave (or plan to leave) the course will be relatively less engaged in the course than other students. In both the unique completer- and leaver-based rules none of the relative features included 'HIGH' levels of student engagement relative to the average student in the course. In total, approximately 47% of relative features included 'MED' levels of student engagement, 30% included 'LOW' levels of student engagement, and 23% included 'HIGH' levels of student engagement relative to the average student in the class. As the relative features with 'HIGH' levels of student engagement were the least in comparison with 'LOW' and 'MED' levels of student engagement, they might have not appeared as much in the rules that uniquely distinguish course completers from the course leavers.

Turning our attention to trends across our findings, the sixth relative feature type '*F6'* (see Table 6) refers to the difference between the time spent by an individual student and the minimum time spent by a student in the class in a particular analysis period (refer to Table 12). This relative feature type appeared the most in both unique completer-based and leaver-based rules. Approximately 51% of relative features of the completer-based rules and 91% of relative features of the leaver-based rules were related to feature '*F6*'. The 91% dominance of F6 appeared in conjunction with 'LOW' levels of student engagement in all the leaver-based unique rules. This particularly makes sense as the relative feature type F6 represents that a student with 'LOW' levels of engagement is close to the minimum time spent by a student in the class on a specific activity.

Table 22. Frequency of Relative Features for Completer- and Leaver-Based Unique Rules

	Completer-based rules		Leaver-based rules	
#	**Relative feature**	**Frequency**	**Relative feature**	**Frequency**
1	F6_quiz.sub1=LOW	20	F6_assignment.sub3=LOW	27
2	F6_quiz1=LOW	12	F6_quiz.sub3=LOW	19
3	F1_quiz1=MED	11	F6_quiz3=LOW	19
4	F6_quiz.sub2=LOW	11	F6_assignment.sub1=LOW	9
5	F6_quiz.sub3=LOW	11	F6_assignment3=LOW	5
6	F1_quiz2=MED	8	F4_assignment.sub2_3=MED	4
7	F1_quiz3=MED	7	F6_attach3=LOW	4
8	F2_quiz1_2=MED	7	F6_quiz.sub2=LOW	4
9	F1_quiz.sub1=MED	6	F3_assignment.sub1_2=MED	3
10	F1_quiz.sub3=MED	6	F6_assignment.sub2=LOW	3
11	F6_quiz2=LOW	6	F6_canvas3=LOW	3
12	F1_quiz.sub2=MED	4	F6_grades3=LOW	3
13	F2_quiz2_3=MED	4	F6_wiki3=LOW	3
14	F6_assignment.sub1=LOW	4	F6_quiz.sub1=LOW	2
15	F6_quiz3=LOW	4	F6_quiz1=LOW	2
16	F2_quiz.sub1_2=MED	3	F5_assignment.sub3=MED	1
17	F6_assignment.sub3=LOW	3	F6_quiz2=LOW	1
18	F7_quiz123=MED	3	F7_grades123=MED	1
19	F3_assignment.sub2_3=MED	2	F8_assignment.sub123=LOW	1
20	F4_assignment.sub1_2=MED	2		
21	F6_assignment.sub2=LOW	2		
22	F1_assignment.sub3=MED	1		
23	F2_quiz.sub2_3=MED	1		
24	F3_assignment.sub1_2=MED	1		
25	F3_quiz.sub2_3=MED	1		
26	F4_quiz.sub1_2=MED	1		
27	F5_quiz.sub2=MED	1		
28	F5_assignment.sub2=MED	1		
29	F5_assignment.sub1=MED	1		

Furthermore, the relative features related to time spent on quizzes, number of quiz submissions, and number of assignment submissions were dominant in both the completer- and the leaver-based rules. This finding echoes the already published work by Crossley et al. (2016) and Cohen (2017), in which in addition to lecture views, assignment submissions and number of assessments distinctively predicted course completers. Also, only 4% (approx.) of leaver-based rules additionally included relative features related to time spent on assignments, grades, wiki pages, attachments, and the course canvas site overall.

Approximately 92% of the relative features that appeared in the leaver-based rules (compared to just 44% of the completer-based rules) were associated with LOW levels of student engagement relative to the average student in the course on different activities on the LMS. This finding supports work from Cohen (2107), which reported that relatively low measurements on different LMS activities (assignment, course view, discussion forum, and resource view) are indicative of dropout cases. Ten relative features were common to both the unique completer- and leaver-based rules, as shown in Table 23. When the relative features listed in Table 13 are removed from the relative features listed in Table 21, some interesting patterns emerge. Only the relative features with “MED” ratings remain for the completer-based rules, and the leaver-based rules are made of mostly relative features with “LOW” ratings. Plus, separately, the leaver-based rules are made of 92% “LOW” ratings whereas half of the completer-based rules don’t have all “LOW” ratings and instead have at least one “MED” rating. This implies that students with a combination of ‘LOW’ and ‘MED’ levels of engagement relative to the average student in the course relate to students persisting and completing the course. On the other hand, students with mostly ‘LOW’ levels of engagement relative to the average student in the course relates to students’ dropping out from the course.

Table 23. Frequency of Common Relative Features for Completer- and Leaver-Based Unique Rules

#	Relative feature	Frequency of appearance among unique rules	
		Completers	**Leavers**
1	F6_quiz.sub1=LOW	20	2
2	F6_quiz1=LOW	12	2
3	F6_quiz.sub2=LOW	11	4
4	F6_quiz.sub3=LOW	11	19
5	F6_quiz2=LOW	6	1
6	F6_assignment.sub1=LOW	4	9
7	F6_quiz3=LOW	4	19
8	F6_assignment.sub3=LOW	3	27
9	F6_assignment.sub2=LOW	2	3
10	F3_assignment.sub1_2=MED	1	3

7. Implications and Future Work

In this section, we present the benefits/implications of this study to researchers interested in the educational data mining space. In addition, we provide potential directions for future work related to this study.

7.1 Benefits

This study includes several potential benefits and the same are presented in this section. The analysis described provides researchers in the educational data mining space a new approach to conduct their own investigations related to online student engagement, an important construct to the study of student persistence in online courses. Because no one correct approach to calculating a student engagement score exists, we recommend researchers to carefully explore and modify the approach to their data in addition to applying our method of evaluating the best online student engagement score to other datasets. Long-term potential implications of such measures include helping online course instructors identify students at-risk of dropping a course.

7.2 Future Work

The work presented in this paper describes a novel approach to numerically represent student engagement among online undergraduate engineering students using their LMS interaction data. Random forest was used to select the relative features used in association rule mining to generate completer-based rules and leaver-based rules. A total of 48 unique completer-based rules and 38 unique leaver-based rules were obtained. The best student engagement score using these rules was found to be the mathematical difference between the percentage of completer rules and the percentage of leaver rules met by each student. The relative features did not include 'HIGH' levels of engagement relative to the average student in the course in both the unique completer- and leaver-based rules, investigating this further could be a potential direction for future work. The relative feature type *F6* appeared the most in both unique completer- and leaver-based rules and the data in this study is not sufficient to provide a rationale for this, hence this needs to be explored further. Next steps for this work include combining the student-LMS interaction data and student attribute data to predict students' persistence decisions i.e., we would like to test whether a model that includes both student-LMS interaction data and student attribute data is superior to a model that uses just either of these in the prediction of students' course-level persistence intentions.

CHAPTER 4

EXAMINING THE IMPACT OF INTERPERSONAL INTERACTIONS ON COURSE-LEVEL PERSISTENCE INTENTIONS AMONG ONLINE UNDERGRADUATE ENGINEERING COURSES

1. Overview

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 the interpersonal interactions within their online courses 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' interpersonal interactions within the course, operationalized as their perceptions of the course LMS dialog, perceptions of instructor practices, and perceptions of peer support in the course. Participants also reported their intentions to persist in the course during each survey administration.

A multi-level modeling analysis revealed that all three student interaction variables - 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. Additionally, interactions between demographic variables and each of the three student interaction variables were significant. Specifically, the effect of perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support on course-level persistence intentions was smaller for veteran than for non-veteran students. The effect of perceptions of instructor perceptions on course-level persistence intentions was smaller for men than for women students. Finally, the effect of perceptions of peer support on course-level persistence was smaller for transfer than for non-transfer students, and for students working full- time than for other students.

2. Introduction

Online education is witnessing an extensive rise in student enrollment (Allen et al., 2016; Seaman et al., 2018). Online education also continues to experience higher percentage of dropouts than the in-person face-to-face programs (Bowers & Kumar, 2015; Shea & Bidjerano, 2016; Gregori, Martínez, & Moyano-Fernández, 2018). Several reasons for students dropping out from the online courses/programs have been documented, including feeling isolated (Robertson, 2020), challenges with balancing academics and personal demands (Müller, 2008; Brown, 2017; Sorensen & Donovan, 2017), inadequate faculty and peer support (Robertson, 2020; St Rose & Moore, 2019), challenges with technology (Müller, 2008; Hart, 2012), and lack of engagement (Müller, 2008; Hart, 2012; Muir, Douglas, & Trimble, 2020). 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 (Muir, Douglas, & Trimble, 2020; Khalid, & Quick, 2016; Bernard et al., 2009). Finally, research also shows that student demographic characteristics such as age, gender, ethnicity, etc. have influenced students' success in online courses (Brown, 2017; D'Amico et al., 2014; Cochran et al., 2014; Tsai et al., 2015; Jenner, 2019).

This study is a part of a larger NSF-funded project studying the persistence of students in online undergraduate engineering courses (Brunhaver et al., 2019). The Model for Online Course-Level Persistence in Engineering (MOCPE) framework, posited by this project, includes factors related to course characteristics and individual characteristics (Lee, Brunhaver, & Bekki; 2020). Lee, et al. (2020) gives a complete treatment of the framework (Lee, Brunhaver, & Bekki; 2020). In this paper, we study the impact of interpersonal interactions within the course on persistence intentions of online undergraduate engineering students. We operationalize interpersonal interactions as students' perceptions of the LMS dialog, instructor practices, and peer support in the course. In addition, we investigate how these relationships change as a function of student demographic variables.

2.1. Course Interpersonal Interactions

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 (Young, 2006). Interpersonal interactions refer to learner-to-learner and learner-to-instructor interactions that take place in the process of both teaching and learning (Moore, 1993; York & Richardson, 2012). 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 (Muir, Douglas, & Trimble, 2020).

Instructor-student and student-student interactions have been shown to critically influence student engagement (Muir, Douglas, & Trimble, 2020; Bernard et al., 2009; Swan et al., 2000; Dixson, 2015), and interpersonal interactions more generally to influence course satisfaction, instructor satisfaction, students' participation, learning, and persistence rates (Khalid, & Quick, 2016; Boston, 2009; Kang & Im, 2013; Cole, Shelley, & Swartz, 2014). Student motivation and cognitive processes are impacted by both instructor-student and student-student interactions (Zimmerman & Schunk, 2008). 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 (Cole, Shelley, & Swartz, 2014; Castaño- Muñoz, Sancho-Vinuesa, & Duart, 2013). Watson et al., (2018) 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 (Garrison, Anderson, & Archer, 2010), in online courses (Hew, Cheung, & Ng, 2010; Cho, & Kim, 2013; Cho, & Cho, 2016).

Student-instructor interactions are helpful in nurturing students' interest towards the course content and associated motivations to learn (Purarjomandlangrudi, Chen, & Nguyen, 2016). Martin et al., (2018), reported that connecting with the instructor, and instructor's own online presence, were significant in enhancing student engagement and learning. In another study (Muir et al., 2019), 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 (Ragusa, & Crampton, 2018) 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 (Luo, Zhang, & Qi, 2017).

Instructor support also plays a significant role in influencing students' decisions about completing or withdrawing from a course. Sorensen and Donovan (Sorensen & Donovan, 2017) reported that participants who believed cited not receiving faculty and advisor support as one of the major reasons for discontinuing the study. Another study (St Rose & Moore, 2019) 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 (Muir, Douglas, & Trimble, 2020; Luo, Zhang, & Qi, 2017). Peer support also has a crucial role in influencing students' persistence decisions in online courses. Robertson (2020) found that the absence of course-facilitated peer interaction was frustrating and isolating to students and influenced students' persistence decisions. Similarly, in another study (Hart, 2012) 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.

The perceptions of dialog in the online learning environment, perceptions of instructor teaching practices and behavior, and perceptions of peer support and connectedness measures were adopted from three different models describing how online course characteristics influence student motivation and engagement: the Attention, Relevance, Confidence, and Satisfaction (ARCS) model of motivational design (Keller, 1987), the Community of Inquiry (COI) model (Garrison, Anderson, & Archer, 2010), and Transactional Distance Theory (TDT) (Moore, 1993). In this study, these measures are proxies for students' perceptions of their interpersonal interactions within their online courses. I.e., "perceptions of instructor practices" is a proxy for students' perceptions of their interpersonal interactions with the instructor; "perceptions of peer support" is a proxy for students' perceptions of their interpersonal interactions with other students; and "perceptions of LMS dialog" is a proxy for the degree to which students perceive that the course learning management system (LMS) facilitates interaction with the instructor and other students. Hence, when we mention interpersonal interactions in this paper, we mean course LMS dialog, instructor practices, and peer support.

2.2 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., (2014) 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 (Tsai et al., 2015). Lin et al., (2019) 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 (Litzler & Young, 2012). The institutional culture has also been shown to play a significant role in influencing transfer students' persistence decisions (Townley et al., 2013). Incorporating instructor and peer mentoring aspects in online learning environments have shown to enhance the persistence of engineering transfer students (Jefferson, Steadman, & Dougherty, 2013; Olson et al., 2016).

Veteran students have been found to be goal-oriented, come with varied useful experiences, motivated, and actively engage in all the assigned learning tasks (Jenner, 2019). Jenner (2019) argues that policies, along with formal and informal programs must be used to strengthen the veteran peer communities stronger. Findings from another study (Everett, 2017) 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 (Bocchi, Eastman, & Swift, 2004), and students' persistence decisions can be influenced by flexibility in their work schedule and support received from the employer (Ivankova & Stick, 2007; Brown, 2017). For students managing the extra time commitments of jobs along with school, time management skills can be particularly essential. Underscoring this, Katiso (2015) showed a significant relationship between motivation levels of achieving academic goals and time management skills of online students.

3. Methods

3.1 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 24 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.

3.2 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 of 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 (GenIUSS Group, 2014; Rivers, 2017). 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 / week) over a duration of 7.5 weeks, which corresponded to the duration of a single online course

Table 24. Demographic Characteristics of the Respondents

Category	*n*	%
Total	152	100
Gender		
Male	117	77
Female	34	22
Genderqueer / Gender non-conforming	01	01
Race/Ethnicity		
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
First Generation Student		
Yes	100	66
No	52	34
Transfer Student		
Yes	120	79
No	32	21
U.S. Armed Forces Veteran		
Yes	44	29
No	108	71
Employment Level		
Working full-time	102	67
Working part-time	27	18
Not working	23	15
Dependent Children		
Yes	54	36
No	98	64
Relationship status		
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

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.

3.3 Instruments

The survey package that participants completed at each survey administration was the MOCPE instrument, which is detailed in Lee, et al. (2020). 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 Appendix F (Lee et al., 2020).

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 25 shows the associated range of Cronbach's α values, all of which indicate that suitable internal consistency reliability was achieved.

Table 25. 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

3.4 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 26.

3.5 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 26. 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.

4. Results

The variations of students’ course persistence intentions in online undergraduate engineering courses were 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 27, 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 27, 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 27. 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 28 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 increases 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 (β=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 (β=-0.1, p=0.005). The interaction plot describing this interaction is shown in Figure 6. 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.

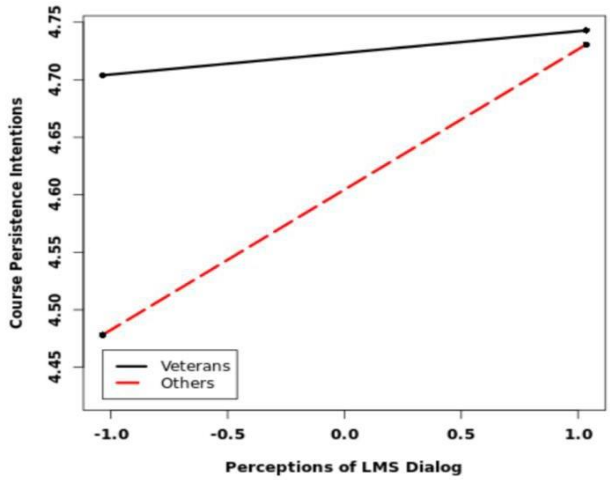

Figure 6. Interaction Effect Between Course LMS Dialog and Veteran Status

Table 28. 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

Table 29 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 increases 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 (β=0.17, p=0.035; β=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 (β=-0.18, $p<0.001$; β=-0.1, $p=0.029$). The interaction plot for the same are shown in Figures 7(a) and 7(b). From Figure 7(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 Figure 7(b), it is observed that, with increase (or decrease) in perceptions of instructor practices there is relatively less increase

Table 29. 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

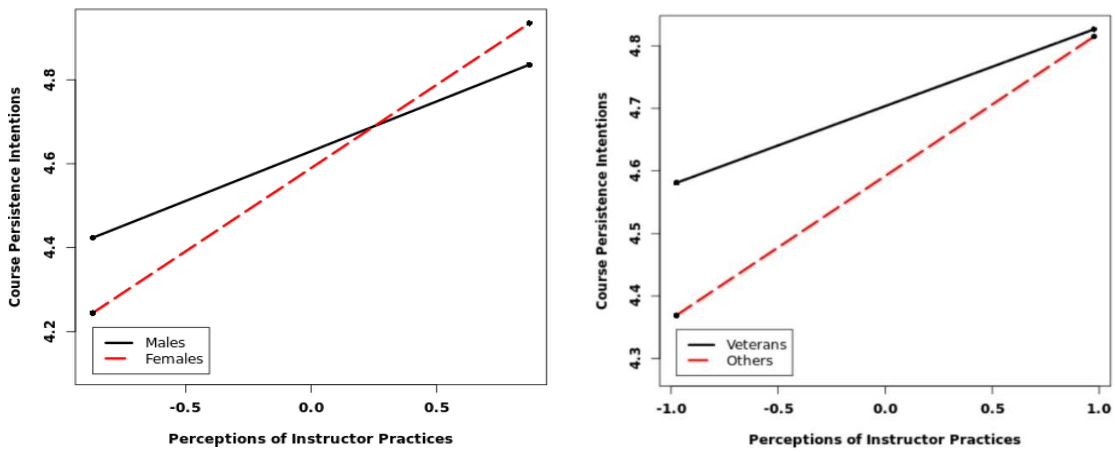

Figure 7. Interaction Effect (a) Between Instructor Practices and Gender, and (b) Between Instructor Practices and Veteran Status

(or decrease) in persistence intentions of veterans than other students.

Table 30 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 increases 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 (β=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 (β=-0.23, $p<0.001$; β=-0.2, p=0.018; β=-0.1, p=0.034). The interaction plot for the same are shown in Figure 8(a), 8(b) and 9. From Figure 8(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 Figure 8(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. From Figure 9, 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.

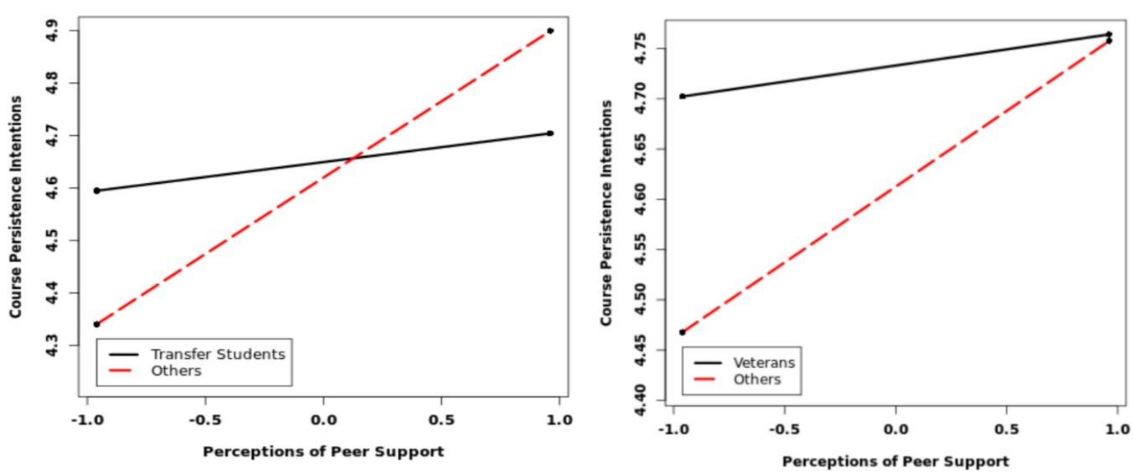

Figure 8. Interaction Effect (a) Between Peer Support and Transfer Student Status, and (b) Between Peer Support and Veteran Status

Table 30. 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

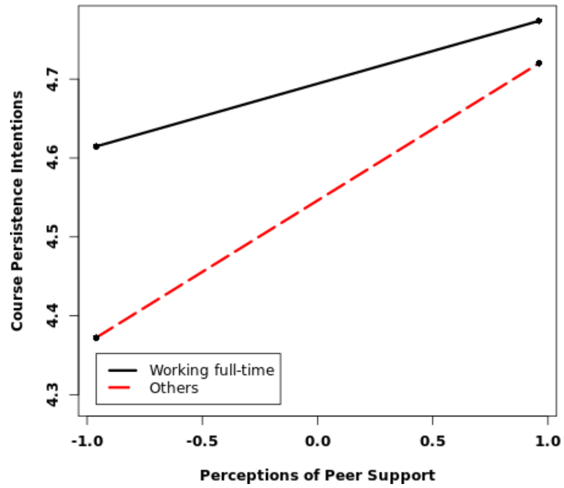

Figure 9. Interaction Effect Between Peer Support and Employment Status

5. Discussion

The results from this study suggest that interpersonal interactions (which we conceptualized here as students' perceptions of course LMS dialog, instructor practices, and peer support) 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 (Hart, 2012; Dixson, 2015), which is linked to persistence (Boston et al., 2009; Quaye, Harper, & Pendakur, 2019; Bekele, 2010; Chen, & Jang, 2010).

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., (2014) 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 (Tsai et al., 2015).

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 (Litzler & Young, 2012). 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 (D'Amico et al., 2014), 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 (Jefferson, Steadman, & Dougherty, 2013; Olson et al., 2016) 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 (Kenner & Weinerman, 2011). 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 (Everett, 2017), 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 (Müller, 2008; Hart, 2012), 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.

6. 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 students' interpersonal interactions in their online courses (perceptions of course LMS dialog, perceptions of instructor practices, and perceptions of peer support). In addition, investigation of how these relationships change 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 would 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.

CHAPTER 5

CONCLUSION

The goal of this dissertation was to better understand the factors that impact the decisions of undergraduate engineering students enrolled in fully online, asynchronous courses to either complete their course or drop out. Three different research methodologies were employed for this study: 1) a systematic literature review to explore the current trends and state of knowledge in online engineering education research (Chapter II), 2) learning analytics and data mining to determine a measure of course-level engagement for undergraduate students enrolled in online engineering courses based on their patterns of engagement with their course learning management system (LMS) (Chapter III), and 3) multilevel modeling to examine the influence of interpersonal interactions on the course-level persistence intentions of undergraduate students enrolled in online engineering courses (Chapter IV). Consistent throughout these studies is a focus on "student engagement and interactions within online engineering courses," which emerged as a theme in the systematic literature review study in Chapter II and served as the motivation for analysis for Chapters III and IV.

The findings from this dissertation advance the existing literature on online engineering education research in several ways. Five themes emerged from the systematic literature review in Chapter II: content design and delivery, engagement and interactions, assessment, feedback, and challenges in online engineering courses.

Implications for both researchers and practitioners accompanied the description of each theme. Additionally, an analysis of current trends in research on online engineering education reveals (i) increasing interest in the online learning format by both researchers and practitioners with time, (ii) a center of gravity for the online engineering education research being conducted globally within the U.S., (iii) broad applicability of online learning within engineering, and (iv) a relatively large scope for creating, testing, and applying research and/or conceptual frameworks in the online engineering learning space. Further, the findings from Chapter III revealed that the best measure of student engagement was determined to be the mathematical difference between the percentages of completer and leaver rules met by each participant. The rules used to compute the students' online course engagement score to predict the course-level persistence intentions of online undergraduate engineering students were generated by applying the association rule mining algorithm to student LMS interaction data. Finally, in Chapter IV, a multi-level modeling analysis revealed that online undergraduate engineering students' course-level persistence intentions were predicted by the quality of their course-related interpersonal interactions, as defined by their perceptions of the course LMS dialog, instructor practices, and peer support. Additionally, the relationships between interpersonal interactions and demographic characteristics indicated that variations in instructor and peer support impact the course-level persistence intentions of non-traditional students (i.e., veteran students, transfer students, and students working full-time) less so than they do the course-level persistence intentions of all other students.

The study includes several implications. The findings of the systematic literature review in Chapter II provide directions for future work for researchers in the online learning field. These include testing and applying different existing frameworks and proposing new frameworks in the online learning space, expanding the generalizability of results from single courses and interventions by engaging instructors from other courses, programs, and institutions in replication and extensionstudies, and conducting more fundamental research in online engineering education to expand current knowledge. Further, the findings of Chapter III can help online instructors measure students' levels of engagement, identify students at risk of dropping out of a course, and make modifications to their instructional design accordingly. Lastly, the findings of Chapter IV can help instructors improve student course-level retention by helping them think about how they might incorporate greater interpersonal interaction into the design of their online courses. In particular, online instructors with flexibility and control in designing the course content could ensure that they include opportunities for students to interact with the course content, their classmates, and the course instructor, as such interactions were shown to promote student online course-level persistence. For example, online instructors can encourage students to interact with the course content by embedding assessments in their lecture videos or requiring students to reflect on their learning after reviewing course material. They can encourage students to interact with peers by incorporating opportunities to collaborate and work in teams for course assignments or projects and incentivizing students to participate in discussion forums and provide constructive criticism on other students' posts. Lastly, students can be encouraged to interact with the instructor by providing students a platform to reach out with questions or concerns related to the course.

Like any other study, this dissertation research also comes with some potential directions for future research. Specific future research directions for each of the themes that emerged as a part of the systematic literature review study are presented in Chapter II. These include: (a) looking at how learners perceive instructional videos categorized as lectures and tutorials and what aspects of these videos help them engage with the course content and enhance their learning, (b) examining how the quality and type of students' interactions in their online course enhance student learning and course completion, (c) investigating how effective assessments used in face-to-face courses are when used in the online learning format and what changes (if any) must be made in the design of assessments to facilitate the adoption of face-to-face learning to the online format, (d)understanding how students perceive automated feedback as compared to the feedback they receive from the instructor, how the quality of automated feedback compares to the feedback they receive from the instructor, and how the differences between automated and instructor feedback impact student learning, and (e) studying the reasons behind challenges students experience in the online engineering space (e.g., feelings of isolation, lack of sense of belongingness, lack of engagement, low persistence intentions) and the factors that influence and mitigate the impact of these challenges. The next steps following the determination of a student engagement score based on student-LMS interaction data in Chapter III include combining student LMS-interaction data with student attribute data to determine whether the combination of student LMS-interaction data and student attribute data provides a more accurate prediction of student online course-level persistence intentions than either type of data alone. Finally, while the findings from Chapter IV indicate that the quality of online students' interpersonal interactions is differentially important to their course-level persistence, depending on their demographic characteristics, the reasons driving this phenomenon were not explored as a part of this dissertation research. Hence, future qualitative research studies will be conducted to investigate how online undergraduate engineering students from varying demographic backgrounds (e.g., by gender identity, racial or ethnic identity, age, etc.) perceive interpersonal interactions in their online courses and how these perceptions influence their decisions to either complete or drop out from their course.

REFERENCES

Agrawal, R., Imieliński, T., & Swami, A. (1993, June). Mining association rules between sets of items in large databases. In *Proceedings of the 1993 ACM SIGMOD international conference on Management of data* (pp. 207-216).

Agrawal, R., Mannila, H., Srikant, R., Toivonen, H., & Verkamo, A. I. (1996). Fast discovery of association rules. *Advances in knowledge discovery and data mining*, *12*(1), 307-328.

Agrawal, R., & Srikant, R. (1994, September). Fast algorithms for mining association rules. In *Proc. 20th int. conf. very large data bases, VLDB* (Vol. 1215, pp. 487-499).

Aguiar, E., Chawla, N. V., Brockman, J., Ambrose, G. A., & Goodrich, V. (2014, March). Engagement vs performance: using electronic portfolios to predict first semester engineering student retention. In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge* (pp. 103-112).

Allen, I. E., & Seaman, J. (2016). *Online report card: Tracking online education in the United States*. Babson Survey Research Group. Babson College, 231 Forest Street, Babson Park, MA 02457.

Allen, I. E., Seaman, J., Poulin, R., & Straut, T. T. (2016). Online report card. *Tracking online education in the United States. Babson Survey Research Group and Quahog Research Group*.

Andersson, C., & Logofatu, D. (2018, April). Implementation of online problem-based learning for mechanical engineering students. In *2018 IEEE Global Engineering Education Conference (EDUCON)* (pp. 484-488). IEEE.

Astatke, Y., & Scott, C. J. (2011, June). Electric circuits online: Towards a completely online electrical engineering curriculum. In *2011 ASEE Annual Conference & Exposition* (pp. 22-545).

Avanzato, R. L. (2017, June). Virtual World Technology to Support Student Collaboration in an Online Engineering Course. In *2017 ASEE Annual Conference & Exposition*.

Azarnoush, B., Bekki, J. M., Bernstein, B. L., & Runger, G. C. (2013, June). An associative based approach to analyzing an online learning environment. In *2013 ASEE Annual Conference & Exposition* (pp. 23-154).

Badjou, S., & Dahmani, R. (2013). Current status of online science and engineering education. *Journal of Online Engineering Education*, *4*(1), 9pp.

Badurdeen, F., Baker, J. R., Rouch, K. E., Goble, C. F., Swan, G. M., Brown, A., & Jawahir, I. S. (2015, June). Development of an Online Master's Degree Program in Manufacturing Systems Engineering. In *2015 ASEE Annual Conference & Exposition* (pp. 26-532).

Balagiu, A., & Sandiuc, C. (2020). Developing an online course for marine engineering. *Scientific Bulletin" Mircea cel Batran" Naval Academy*, *23*(1), 282A-286.

Balakrishnan, G., & Coetzee, D. (2013). Predicting student retention in massive open online courses using hidden markov models. *Electrical Engineering and Computer Sciences University of California at Berkeley*, *53*, 57-58.

Batanero, C., de-Marcos, L., Holvikivi, J., Hilera, J. R., & Otón, S. (2019). Effects of new supportive technologies for blind and deaf engineering students in online learning. *IEEE Transactions on Education*, *62*(4), 270-277.

Baytiyeh, H., & Naja, M. (2012). Identifying the challenging factors in the transition from colleges of engineering to employment. *European Journal of Engineering Education*, *37*(1), 3-14.

Bekele, T. A. (2010). Motivation and satisfaction in internet-supported learning environments: A review. *Journal of Educational Technology & Society*, *13*(2), 116-127.

Bernard, R. M., Abrami, P. C., Borokhovski, E., Wade, C. A., Tamim, R. M., Surkes, M. A., & Bethel, E. C. (2009). A meta-analysis of three types of interaction treatments in distance education. *Review of Educational research*, *79*(3), 1243-1289.

Bir, D. D., & Ahn, B. (2017, June). Examining student attitudes to improve an undergraduate online engineering course. In *2017 ASEE Annual Conference & Exposition*.

Bocchi, J., Eastman, J. K., & Swift, C. O. (2004). Retaining the online learner: Profile of students in an online MBA program and implications for teaching them. *Journal of education for Business*, *79*(4), 245-253.

Bohan, J., & Stack, N. (2014). Do weekly on-line homework assignments promote student engagement and enhance learning in first year psychology students?. *Psychology of Education Review*, *38*(2).

Borrego, M., Douglas, E. P., & Amelink, C. T. (2009). Quantitative, qualitative, and mixed research methods in engineering education. *Journal of Engineering education*, *98*(1), 53-66.

Borrego, M., Foster, M. J., & Froyd, J. E. (2014). Systematic literature reviews in engineering education and other developing interdisciplinary fields. *Journal of Engineering Education*, *103*(1), 45-76.

Boston, W., Díaz, S. R., Gibson, A. M., Ice, P., Richardson, J., & Swan, K. (2009). An exploration of the relationship between indicators of the community of inquiry framework and retention in online programs.

Bote-Lorenzo, M. L., & Gómez-Sánchez, E. (2017, March). Predicting the decrease of engagement indicators in a MOOC. In *Proceedings of the Seventh international learning analytics & knowledge conference* (pp. 143-147).

Bowers, J., & Kumar, P. (2015). Students' perceptions of teaching and social presence: A comparative analysis of face-to-face and online learning environments. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT)*, *10*(1), 27-44.

Boyer, S., & Veeramachaneni, K. (2015, June). Transfer learning for predictive models in massive open online courses. In *International conference on artificial intelligence in education* (pp. 54-63). Springer, Cham.

Bozkurt, I., & Helm, J. (2013). Development and Application of a Systems Engineering Framework to Support Online Course Design and Delivery. *Advances in Engineering Education*, *3*(3), n3.

Brown, C. G. (2017). The Persistence and Attrition of Online Learners. *School Leadership Review*, *12*(1), 7.

Brunhaver, S., Bekki, J., Lee, E., & Kittur, J. (2019, March). Understanding the factors contributing to persistence among undergraduate engineering students in online courses. In *Companion Proceedings of the 9th International Conference on Learning Analytics & Knowledge*.

Castaño-Muñoz, J., Sancho-Vinuesa, T., & Duart, J. M. (2013). Online interaction in higher education: Is there evidence of diminishing returns?. *International Review of Research in Open and Distributed Learning*, *14*(5), 240-257.

Chatman Jr, T. E. (2020). Understanding the Relationship Between Student Engagement and Persistence Among Community College Students.

Chatterjee, R., Kamal, A. E., & Wang, Z. (2016, June). Alternate Assessments to Support Formative Evaluations in an Asynchronous Online Computer Engineering Graduate Course. In *2016 ASEE Annual Conference & Exposition*.

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, *16*, 321-357.

Chen, B., Bastedo, K., & Howard, W. (2018). Exploring Design Elements for Online STEM Courses: Active Learning, Engagement & Assessment Design. *Online Learning*, *22*(2), 59-75.

Chen, K. C., & Jang, S. J. (2010). Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behavior*, *26*(4), 741-752.

Cho, M. H., & Kim, B. J. (2013). Students' self-regulation for interaction with others in online learning environments. *The Internet and Higher Education*, *17*, 69-75.

Cho, M. H., & Cho, Y. (2016). Online instructors' use of scaffolding strategies to promote interactions: A scale development study. *International Review of Research in Open and Distributed Learning: IRRODL*, *17*(6), 108-120.

Clapton, J., Rutter, D., & Sharif, N. (2009). SCIE Systematic mapping guidance. *London: SCIE*.

Crossley, S., Paquette, L., Dascalu, M., McNamara, D. S., & Baker, R. S. (2016, April). Combining click-stream data with NLP tools to better understand MOOC completion. In *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 6-14).

Coates, H. (2007). A model of online and general campus-based student engagement. *Assessment & Evaluation in Higher Education*, *32*(2), 121-141.

Cochran, J. D., Campbell, S. M., Baker, H. M., & Leeds, E. M. (2014). The role of student characteristics in predicting retention in online courses. *Research in Higher Education*, *55*(1), 27-48.

Cohen, A. (2017). Analysis of student activity in web-supported courses as a tool for predicting dropout. *Educational Technology Research and Development*, *65*(5), 1285-1304.

Cole, M. T., Shelley, D. J., & Swartz, L. B. (2014). Online instruction, e-learning, and student satisfaction: A three year study. *The International Review of Research in Open and Distributed Learning*, *15*(6).

Cooper, M. E., Bullard, L. G., Spencer, D., & Willis, C. (2020). Direct and Indirect Assessment of Student Perspectives and Performance in an Online/Distance Education Chemical Engineering Bridging Course Sequence. *Chemical Engineering Education*, *54*(2), 59-70.

D'Amico, M. M., Dika, S. L., Elling, T. W., Algozzine, B., & Ginn, D. J. (2014). Early integration and other outcomes for community college transfer students. Research in Higher Education, 55, 370–399.

Danaher, M. (2014, December). Online engineering courses: Benchmarking quality. In *2014 International Conference on Interactive Collaborative Learning (ICL)* (pp. 1079-1086). IEEE.

de la Torre, L., Sàenz, J., Chaos, D., Sánchez, J., & Dormido, S. (2020). A Master Course on Automatic Control Based on the Use of Online Labs. *IFAC-PapersOnLine*, *53*(2), 17542-17547.

Dixson, M. D. (2015). Measuring student engagement in the online course: The Online Student Engagement scale (OSE). *Online Learning*, *19*(4), n4.

Everett, M. S. (2017). The Persistence of Military Veteran Students in a Southeastern Community College: A Narrative Study.

Fatehiboroujeni, S., Qattawi, A., & Goyal, S. (2019, June). Assessing and Improving Student Engagement and Motivation in Mechanical Engineering Online Courses. In *2019 ASEE Annual Conference & Exposition*.

Fei, M., & Yeung, D. Y. (2015, November). Temporal models for predicting student dropout in massive open online courses. In *2015 IEEE International Conference on Data Mining Workshop (ICDMW)* (pp. 256-263). IEEE.

Fovet, F. (2020). Universal Design for Learning as a Tool for Inclusion in the Higher Education Classroom: Tips for the Next Decade of Implementation. *Education Journal*, *9*(6), 163-172.

Fu, P. (2019, June). Trifecta of Engagement in an Online Engineering Management Course. In *2019 ASEE Annual Conference & Exposition*.

Garrison, D. R., Anderson, T., & Archer, W. (2010). The first decade of the community of inquiry framework: A retrospective. *The internet and higher education*, *13*(1-2), 5-9.

GenIUSS Group. (2014). *Best practices for asking questions to identify transgender and other gender minority respondents on population-based surveys*. eScholarship, University of California.

Gercek, G., Saleem, N., & Steel, D. J. (2016). Implementing Cloud Based Virtual Computer Network Labs for Online Education: Experiences from a Phased Approach. *International Journal of Online Engineering*, *12*(3).

Gregori, P., Martínez, V., & Moyano-Fernández, J. J. (2018). Basic actions to reduce dropout rates in distance learning. *Evaluation and program planning*, *66*, 48-52.

Hachey, A. C., Wladis, C., & Conway, K. (2015). Prior online course experience and GPA as predictors of subsequent online STEM course outcomes. *The Internet and Higher Education*, *25*, 11-17.

Halada, G. P. (2017, June). Learning from Engineering Disasters: A Multidisciplinary Online Course. In *2017 ASEE Annual Conference & Exposition*.

Halawa, S., Greene, D., & Mitchell, J. (2014). Dropout prediction in MOOCs using learner activity features. *Proceedings of the second European MOOC stakeholder summit*, *37*(1), 58-65.

Hammout, N., & Hosseini, S. (2020, April). Involvement of students in online master's studies of Engineering and Science: a path to minimize the gender gap in STEM. In *2020 IEEE Global Engineering Education Conference (EDUCON)* (pp. 273-278). IEEE.

Hart, C. (2012). Factors associated with student persistence in an online program of study: A review of the literature. *Journal of interactive online learning*, *11*(1).

Henrie, C. R., Bodily, R., Larsen, R., & Graham, C. R. (2018). Exploring the potential of LMS log data as a proxy measure of student engagement. *Journal of Computing in Higher Education*, *30*(2), 344-362.

Hew, K. F., Cheung, W. S., & Ng, C. S. L. (2010). Student contribution in asynchronous online discussion: A review of the research and empirical exploration. *Instructional science, 38*(6), 571-606.

Humber, J. F. (2018). *Student engagement in online courses: A grounded theory case study*. The University of Alabama.

Ivankova, N. V., & Stick, S. L. (2007). Students' persistence in a distributed doctoral program in educational leadership in higher education: A mixed methods study. *Research in Higher Education*, *48*(1), 93-135.

James, K. L., Randall, N. P., & Haddaway, N. R. (2016). A methodology for systematic mapping in environmental sciences. *Environmental evidence*, *5*(1), 1-13.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112, p. 18). New York: springer.

Jefferson, G., Steadman, S., & Dougherty, F. (2013). Transfer student transition: Lessons learned. *Proceedings of the American Society for Engineering Education Annual Conference.*

Jenner, B. (2019). Student veterans in transition: The impact of peer community. *Journal of The First-Year Experience & Students in Transition*, *31*(1), 69-83.

Kang, M., & Im, T. (2013). Factors of learner–instructor interaction which predict perceived learning outcomes in online learning environment. *Journal of Computer Assisted Learning*, *29*(3), 292-301.

Kara, N. (2021). A Systematic Review of the Use of Serious Games in Science Education. *Contemporary Educational Technology*, *13*(2), ep295.

Karaksha, A., Grant, G., Anoopkumar-Dukie, S., Nirthanan, S. N., & Davey, A. K. (2013). Student engagement in pharmacology courses using online learning tools. *American journal of pharmaceutical education*, *77*(6).

Katiso, A. E. (2015). Online adult students' time management skills and their academic achievement and persistence: Technology-based learning and student success.

Keller, J. M. (1987). Development and use of the ARCS model of instructional design. *Journal of instructional development*, *10*(3), 2-10.

Kenner, C., & Weinerman, J. (2011). Adult learning theory: Applications to non-traditional college students. *Journal of College Reading and Learning*, *41*(2), 87-96.

Khalid, M. N., & Quick, D. (2016). Teaching Presence Influencing Online Students' Course Satisfaction at an Institution of Higher Education. *International Education Studies*, *9*(3), 62-70.

Kiridena, S. B., Samaranayake, P., & Hastie, D. B. (2014, December). Instructional design for online course delivery in engineering management: synthesizing learning styles, pedagogical perspectives and contingency factors. In *2014 IEEE International Conference on Industrial Engineering and Engineering Management* (pp. 1198-1203). IEEE.

Kittur, J., Bekki, J., & Brunhaver, S. (2021). Development of a student engagement score for online undergraduate engineering courses using learning management system interaction data. *Computer Applications in Engineering Education*.

Kittur, J., Bekki, J., & Brunhaver, S. (2020, January). Learner Analytics in Engineering Education: A Detailed Account of Practices Used in the Cleaning and Manipulation of Learning Management System Data from Online Undergraduate Engineering Courses. In *Proceedings of the American Society for Engineering Education*.

Kizilcec, R. F., Piech, C., & Schneider, E. (2013, April). Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. In *Proceedings of the third international conference on learning analytics and knowledge* (pp. 170-179).

Kocdar, S., Bozkurt, A., & Goru Dogan, T. (2021). Engineering through distance education in the time of the fourth industrial revolution: Reflections from three decades of peer reviewed studies. *Computer Applications in Engineering Education*, *29*(4), 931-949.

Ladson-Billings, G. (1995). Toward a theory of culturally relevant pedagogy. *American educational research journal*, *32*(3), 465-491.

Lakshmi, T. J., & Prasad, C. S. R. (2014, August). A study on classifying imbalanced datasets. In *2014 First International Conference on Networks & Soft Computing (ICNSC2014)* (pp. 141-145). IEEE.

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *biometrics*, 159-174.

Lawton, D., Vye, N., Bransford, J., Sanders, E., Richey, M., French, D., & Stephens, R. (2012). Online learning based on essential concepts and formative assessment. *Journal of Engineering Education*, *101*(2), 244-287.

Lee, E., Brunhaver, S., & Bekki, J. (2020, January). Developing an Instrument to Measure Online Engineering Undergraduate Students' Learning Experiences and Intentions to Persist. In *Proceedings of the American Society for Engineering Education*

Levy, Y., & Ramim, M. M. (2017). The e-learning skills gap study: Initial results of skills desired for persistence and success in online engineering and computing courses. In *Proceeding of the Chais 2017 Conference on Innovative and Learning Technologies Research* (pp. 57-68).

Lin, Y., Dowell, N., Godfrey, A., Choi, H., & Brooks, C. (2019, March). Modeling gender dynamics in intra and interpersonal interactions during online collaborative learning. In *Proceedings of the 9th international conference on learning analytics & knowledge* (pp. 431-435).

Litzler, E., & Young, J. (2012). Understanding the risk of attrition in undergraduate engineering: Results from the Project to Assess Climate in Engineering. *Journal of Engineering Education*, *101(2)*, 319-345.

Liu, B., Hsu, W., & Ma, Y. (1998, August). Integrating classification and association rule mining. In *Kdd* (Vol. 98, pp. 80-86).

Lu, J., Yu, C. S., & Liu, C. (2003). Learning style, learning patterns, and learning performance in a WebCT-based MIS course. *Information & Management*, *40*(6), 497-507.

Luo, N., Zhang, M., & Qi, D. (2017). Effects of different interactions on students' sense of community in e-learning environment. *Computer & Education* (pp. 153-160)

Mansor, M. S. A., & Ismail, A. (2012). Learning styles and perception of engineering students towards online learning. *Procedia-Social and Behavioral Sciences*, *69*, 669-674.

Martin, F., Wang, C., & Sadaf, A. (2018). Student perception of helpfulness of facilitation strategies that enhance instructor presence, connectedness, engagement and learning in online courses. *The Internet and Higher Education*, *37*, 52-65.

Matzakos, N. M., & Kalogiannakis, M. (2018). An analysis of first year engineering students' satisfaction with a support distance learning program in mathematics. *Education and Information Technologies*, *23*(2), 869-891.

McClanahan, J. L. (2018). *Culturally relevant pedagogy and its impact on student belonging* (Doctoral dissertation, University of North Carolina at Greensboro).

Me, Y. Z. (2020). A Cross-Referencing System for Curriculum Coordination in Multi-Institution Online Graduate Engineering Degree Programs: Case Study of the Virginia Engineering Online Program. In *Proceedings of the International Annual Conference of the American Society for Engineering Management.* (pp. 1-6). American Society for Engineering Management (ASEM).

Minichiello, A., Legler, N., Hailey, C., & Adams, V. D. (2013, October). Online engineering course design, Part I: Toward asynchronous, web-based delivery of a first course in thermodynamics. In *2013 IEEE Frontiers in Education Conference (FIE)* (pp. 1928-1934). IEEE.

Mohamad, N., Ahmad, N. B., & Sulaiman, S. (2017). Data pre-processing: a case study in predicting student's retention in MOOC. *Journal of Fundamental and Applied Sciences*, *9*(4S), 598-613.

Moore, L. R. (2021). Developing Teachers' Ability to Provide Culturally Relevant Pedagogy.

Moore, MJ (1993), 'Three types of interaction', in K Harry, M John & D Keegan (eds.), *Distance Education Theory*, Routledge, New York, pp. *19-24*.

Moore, M.G., 'Theory of transactional distance,' *Theoretical Principles of Distance Education*, vol. 1, pp. 22-38, 1993.

Moreno-Marcos, P. M., Munoz-Merino, P. J., Alario-Hoyos, C., & Delgado Kloos, C. (2020). Re-defining, analyzing and predicting persistence using student events in online learning. *Applied Sciences*, *10*(5), 1722.

Morris, L. V., & Finnegan, C. L. (2008). Best practices in predicting and encouraging student persistence and achievement online. *Journal of College Student Retention: Research, Theory & Practice*, *10*(1), 55-64.

Muir, T., Douglas, T., & Trimble, A. (2020). Facilitation strategies for enhancing the learning and engagement of online students. *Journal of University Teaching & Learning Practice*, *17*(3), 8.

Muir, T., Milthorpe, N., Stone, C., Dyment, J., Freeman, E., & Hopwood, B. (2019). Chronicling engagement: students' experience of online learning over time. *Distance Education*, *40*(2), 262-277.

Müller, T. (2008). Persistence of women in online degree-completion programs. *The International Review of Research in Open and Distributed Learning*, *9*(2).

Odom, P. W., Merzdorf, H. E., Montalvo, F. J., & Davis, J. M. (2019, June). Analysis of Student Engagement Data from US News & World Report Regarding Online Graduate Engineering Programs. In *2019 ASEE Annual Conference & Exposition*.

Olson, L., Moll, A., Bullock, D., Jain, A., & Callahan, J. (2016). Support model for transfer students utilizing the STEM scholarship program. *Proceedings of the American Society for Engineering Education Annual Conference.*

Pamplona, S., Seoane, I., & Bravo-Agapito, J. (2018, October). Assessing conceptual knowledge in three online engineering courses: theory of computation and compiler construction, operating systems, and signal and systems. In *Proceedings of the First International Conference on Data Science, E-learning and Information Systems* (pp. 1-6).

Pawley, A. L. (2017). Shifting the "default": The case for making diversity the expected condition for engineering education and making whiteness and maleness visible. *Journal of Engineering Education*, *106*(4), 531-533.

Pedrosa, D., Morgado, L., Cravino, J., Fontes, M. M., Castelhano, M., Machado, C., & Curado, E. (2020, June). Challenges implementing the SimProgramming approach in online software engineering education for promoting self and co-regulation of learning. In *2020 6th International Conference of the Immersive Learning Research Network (iLRN)* (pp. 236-242). IEEE.

Perales Jarillo, M., Pedraza, L., Moreno Ger, P., & Bocos, E. (2019). Challenges of online higher education in the face of the Sustainability Objectives of the United Nations: Carbon footprint, accessibility and social inclusion. *Sustainability*, *11*(20), 5580.

Petty, T., & Farinde, A. (2013). Investigating student engagement in an online mathematics course through windows into teaching and learning. *Journal of Online Learning and Teaching*, *9*(2), 261-270.

Pilotti, M. A., & Al Mubarak, H. (2021). Systematic versus informal application of culturally relevant pedagogy: Are performance outcomes different? A study of college students. *Journal of Culture and Values in Education*, *4*(2), 14-26.

Pohl, L. M., & Walters, S. (2015, June). Instructional Videos in an Online Engineering Economics Course. In *2015 ASEE Annual Conference & Exposition* (pp. 26-979).

Purarjomandlangrudi, A., Chen, D., & Nguyen, A. (2016). Investigating the Drivers of Student Interaction and Engagement in Online Courses: A Study of State-of-the-art. *Informatics in Education*, 2016, Vol. 15, No. 2, 269–286.

Purwar, A., & Scott, C. A. (2019, June). An online engineering dynamics class for college sophomores: Design, implementation, and assessment. In *2019 ASEE Annual Conference & Exposition*.

Quaye, S. J., Harper, S. R., & Pendakur, S. L. (Eds.). (2019). *Student engagement in higher education: Theoretical perspectives and practical approaches for diverse populations*. Routledge.

Ragusa, A. T., & Crampton, A. (2018). Sense of connection, identity and academic success in distance education: Sociologically exploring online learning environments. *Rural Society*, *27*(2), 125-142.

Rahim, A. H. A., Rashid, N. A., Nayan, A., & Ahmad, A. R. (2019). Smote approach to imbalanced dataset in logistic regression analysis. In *Proceedings of the Third*

International Conference on Computing, Mathematics and Statistics (iCMS2017) (pp. 429-433). Springer, Singapore.

Richardson, J. C., & Newby, T. (2006). The role of students' cognitive engagement in online learning. *American Journal of Distance Education*, *20*(1), 23-37.

Rivers, E. (2017). Women, minorities, and persons with disabilities in science and engineering. *National Science Foundation*.

Robertson, S. G. (2020). Factors That Influence Students' Decision to Drop Out of an Online Business Course. (*Dissertation Thesis*)

Romero, C., & Ventura, S. (2010). Educational data mining: a review of the state of the art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, *40*(6), 601-618.

Rutz, E., & Ehrlich, S. (2016, June). Increasing learner engagement in online learning through use of interactive feedback: results of a pilot study. In *2016 ASEE Annual Conference & Exposition*.

Salvo, S. G., Shelton, K., & Welch, B. (2019). African American males learning online: Promoting academic achievement in higher education. *Online Learning*, *23*(1), 22-36.

Sancho-Vinuesa, T., Masià, R., Fuertes-Alpiste, M., & Molas-Castells, N. (2018). Exploring the effectiveness of continuous activity with automatic feedback in online calculus. *Computer Applications in Engineering Education*, *26*(1), 62-74.

Sanger, C. S. (2020). Inclusive pedagogy and universal design approaches for diverse learning environments. In *Diversity and inclusion in global higher education* (pp. 31-71). Palgrave Macmillan, Singapore.

Schutz, D. M., Kim, Y. Y., & Dionne, D. (2018, June). Factors Influencing Student Veteran Participation in Online Engineering Education. In *2018 ASEE Annual Conference & Exposition*.

Seaman, J. E., Allen, I. E., & Seaman, J. (2018). Grade increase: Tracking distance education in the United States. *Babson Survey Research Group*.

Sezgin, S., & Sevim Cirak, N. (2021). The role of MOOCs in engineering education: An exploratory systematic review of peer-reviewed literature. *Computer Applications in Engineering Education*, *29*(4), 950-968.

Shea, P., & Bidjerano, T. (2016). A national study of differences between online and classroom-only community college students in time to first associate degree attainment, transfer, and dropout. *Online Learning*, *20*(3), 14-15.

Shelton, B. E., Hung, J. L., & Lowenthal, P. R. (2017). Predicting student success by modeling student interaction in asynchronous online courses. *Distance Education*, *38*(1), 59-69.

Siddhpura, A., & Siddhpura, M. (2020, December). Plagiarism, Contract Cheating And Other Academic Misconducts In Online Engineering Education: Analysis, Detection And Prevention Strategies. In *2020 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)* (pp. 112-119). IEEE.

Sneed, O. (2019). *Fostering Student Engagement through an Online Community of Learning: A Mixed Methods Action Research Dissertation*. Arizona State University.

Sorensen, C., & Donovan, J. (2017). An examination of factors that impact the retention of online students at a for-profit university. *Online Learning*, *21*(3), 206-221.

St Rose, M., & Moore, A. (2019). Student Retention in Online Courses: University Role. *Online Journal of Distance Learning Administration*, *22*(3), n3.

Stewart, M., Stott, T., & Nuttall, A. M. (2011). Student engagement patterns over the duration of level 1 and level 3 geography modules: Influences on student attendance, performance and use of online resources. *Journal of Geography in Higher Education*, *35*(01), 47-65.

Sun, Y., Wong, A. K., & Wang, Y. (2006). An overview of associative classifiers. *DMIN*, 138-143.

Swan, K., Shea, P., Fredericksen, E., Pickett, A., Pelz, W., & Maher, G. (2000). Building knowledge building communities: Consistency, contact and communication in the virtual classroom. Journal of Educational Computing Research, 23(4), 359–383.

Tan, P. N., Steinbach, M., & Kumar, V. (2016). *Introduction to data mining*. Pearson Education India.

Taylor, C. (2014). *Stopout prediction in massive open online courses* (Doctoral dissertation, Massachusetts Institute of Technology).

Team, R. C. (2013). R: A language and environment for statistical computing. *R Foundation for Statistical Computing.* URL https://www.R-project.org/.

Townley, G., Katz, J., Wandersman, A., Skiles, B., Schillaci, M., Timmerman, B., & Mousseau, T. (2013). Exploring the role of sense of community in the undergraduate transfer student experience. Journal of Community Psychology, 41(3), 277–290.

Trumbore, A. (2014). Rules of engagement: Strategies to increase online engagement at scale. *Change: The Magazine of Higher Learning*, *46*(4), 38-45.

Tsai, M. J., Liang, J. C., Hou, H. T., & Tsai, C. C. (2015). Males are not as active as females in online discussion: Gender differences in face-to-face and online discussion strategies. *Australasian Journal of Educational Technology*, *31*(3).

Uribe, M. D. R., Magana, A. J., Bahk, J. H., & Shakouri, A. (2016). Computational simulations as virtual laboratories for online engineering education: A case study in the field of thermoelectricity. *Computer Applications in Engineering Education*, *24*(3), 428-442.

van de Vegte, J. (2017, July). Intercultural engineering online: Getting humanitarian engineering on the agenda. In *2017 IEEE Canada International Humanitarian Technology Conference (IHTC)* (pp. 80-84). IEEE.

Vytasek, J. M., Patzak, A., & Winne, P. H. (2020). Analytics for student engagement. In *Machine learning paradigms* (pp. 23-48). Springer, Cham.

Wise, A. F., Vytasek, J. M., Hausknecht, S., & Zhao, Y. (2016). Developing Learning Analytics Design Knowledge in the" Middle Space": The Student Tuning Model and Align Design Framework for Learning Analytics Use. *Online Learning*, *20*(2), 155-182.

Watson, M., & Ferdinand-James, D. (2018, April). Unpacking the influence of online students' perceived course satisfaction/dissatisfaction on their performance. *Murray State University*

Watts, J. (2019). Assessing an online student orientation: Impacts on retention, satisfaction, and student learning. *Technical Communication Quarterly*, *28*(3), 254-270.

Yang, D. (2017). Instructional strategies and course design for teaching statistics online: perspectives from online students. *International Journal of STEM Education*, *4*(1), 1-15.

York, C. S., & Richardson, J. C. (2012). Interpersonal Interaction in Online Learning: Experienced Online Instructors' Perceptions of Influencing Factors. *Journal of Asynchronous Learning Networks*, *16*(4), 83-98.

Young, S. (2006). Student views of effective online teaching in higher education. American Journal of Distance Education, 20(2), 65–77.

Young, S., & Bruce, M. A. (2011). Classroom community and student engagement in online courses. *Journal of Online Learning and Teaching*, *7*(2), 219-230

Yousuf, B., & Conlan, O. (2017). Supporting student engagement through explorable visual narratives. *IEEE Transactions on Learning Technologies*, *11*(3), 307-320.

Zeng, X., Yu, C., Liu, Y., Hu, X., Hao, Q., Jiang, Y., ... & Teng, B. (2018). The construction and online/offline blended learning of small private online courses of Principles of Chemical Engineering. *Computer Applications in Engineering Education*, *26*(5), 1519-1526.

Zimmerman, B. J., & Schunk, D. H. (2008). An essential dimension of self-regulated learning. *Motivation and self-regulated learning: Theory, research, and applications*, *1*, 1-30.

APPENDIX A

CODES, CODE DESCRIPTION, AND EXEMPLARS

Code	Description	Exemplar
Assessment	Topics related to course assessments including quizzes, assignments, exams, projects, etc. in online engineering courses. Other topics include assessment of students' conceptual knowledge, misconceptions, and academic misconducts in online engineering courses/programs.	"Student Assessment of Learning Gains survey" (Halada, 2017)
Feedback	Topics related to different types of feedback including the feedback provided by the instructor to students using different approaches such as text-based, interactive, or automated feedback, student feedback about the instructor's teaching approaches and the overall course.	"The first investigation was completed during the 2013-2014 academic year and included 40 students. During the first half of the semester students received text-based feedback on their written assignments (this method had been used by the instructor for the previous five years). During the second half of the semester, students received interactive feedback on their written assignments. In all cases the feedback was provided to the students via the university's leaning management system." (Rutz & Ehrlich, 2016)
Attrition or Enrollment	Topics referring to student enrollment, dropout, and attrition in online education.	"Actively participating students seems to be one of the success factors for avoiding dropouts in online courses as well as a strong sense of responsibility and community with the group." (Andersson & Logofatu, 2018)
Class Design or Structure	Topics related to overall class design such as topics being covered, targeted academic level, and projects.	"The digital systems course was a 15-week lecture online course that covered Boolean algebra, logic gates, combinational logic, minimization, number systems, MSI devices, sequential circuits, finite state machines, memory and programmable logic devices, and FPGA technology." (Avanzato, 2017)

Content Delivery	Topics related to the delivery of course content online such as through lecture videos	"An online version of the class consisting of topical videos of the lecture, on-line quizzes and homework, and assessments could 1) facilitate self-study and -pacing of the material on part of students, 2) enable problem solving and critical discussion between students and instructors using an online forum, and 3) scale-up the class to reach a large number of students." (Purwar & Scott, 2019)
Engagement	Topics describing course engagement throughout the course (engagement with the course, peers, the instructor, etc.)	"Various approaches are adopted to improve student participation, such as integration of quizzes in the instructional lectures, use of discussion boards, and offering synchronous review sessions." (Fatehiboroujeni, Qattawi, & Goyal, 2019)
Laboratory Design	Topics related to developing online laboratories and simulations to mimic in-person hands-on experiences	"It was found at the colloquy that, surprisingly, common there was no clear and definition among engineering educators of what exactly the objectives of laboratory experimentation are. So, the teaching of laboratory experience online could not even be addressed without first defining what those objectives are for onsite laboratory experiments." (Badjou & Dahmani, 2013)
Learning Technology	Topics related to a specific implementation of a technology for the course but not limited to learning management systems (LMS) like Blackboard or Canvas	"Panopto Focus" (Astatke & Scott, 2011); "Moodle" (Pedrosa et al., 2020)
Pedagogical Considerations	Topics regarding specific pedagogies and instructional practices that engineering educators are implementing in the online format	"This study focuses on using problem-based learning in online lab classes for mechanical engineering students" (Andersson & Logofatu, 2018)
Recommendations	Strategies and recommendations for enhancing the online experiences of students and instructors	"Keep Videos Short" (Pohl & Walters, 2015)

Technical Challenges	Topics describing technical challenges encountered by students or instructors in the online course	"Technical Complaints: In topic 2, on March 23rd, a student reported that an API registration was missing from the repository where he had posted it. This can be an actual technical glitch or a misinterpretation of repository operation" (Pedrosa et al., 2020)
Time Challenges	Topics that mention challenges related to time or timing, such as time spent by the instructor developing the course or time spent by the students attempting to complete the course	"Our study demonstrates that students invest significant time on lecture videos, homework, quizzes, and projects" (Fatehiboroujeni, Qattawi, & Goyal, 2019)

APPENDIX B

CLASSIFICATION OF THE REVIEWED STUDIES BASED ON SPECIFIC THEMES

Theme 1: Content design and delivery

Authors	*Country affiliation of first author*	*Title*
Pohl, L. M., & Walters, S. (2015)	United States	Instructional Videos in an Online Engineering Economics Course
Halada, G. P. (2017)	United States	Learning from Engineering Disasters: A Multidisciplinary Online Course
Andersson, C., & Logofatu, D. (2018)	Germany	Implementation of Online Problem-Based Learning for Mechanical Engineering Students
Fatehiboroujeni, S., Qattawi, A., & Goyal, S. (2019)	United States	Assessing and Improving Student Engagement and Motivation in Mechanical Engineering Online Courses
Uribe, M. D. R., Magana, A. J., Bahk, J. H., & Shakouri, A. (2016)	United States	Computational Simulations as Virtual Laboratories for Online Engineering Education: A Case Study in the Field of Thermoelectricity
Pedrosa, D., Morgado, L., Cravino, J., Fontes, M. M., Castelhano, M., Machado, C., & Curado, E. (2020)	Portugal	Challenges Implementing the SimProgramming Approach in Online Software Engineering Education for Promoting Self and Co-regulation of Learning
Purwar, A., & Scott, C. A. (2019)	United States	An Online Engineering Dynamics Class for College Sophomores: Design, Implementation, and Assessment
Astatke, Y., & Scott, C. J. (2011)	United States	Electric Circuits Online – Towards a Completely Online Electrical Engineering Curriculum
Zhang, Y. (2020)	United States	A Cross-Referencing System for Curriculum Coordination in Multi-Institution Online Graduate Engineering Degree Programs: Case Study of the Virginia Engineering Online Program
Balagiu, A., & Sandiuc, C. (2020)	Romania	Developing an online course for marine engineering
Badjou, S., & Dahmani, R. (2013)	United States	Current Status of Online Science and Engineering Education
Chen, B., Bastedo, K., & Howard, W. (2018)	United States	Exploring Design Elements for Online STEM Courses: Active Learning, Engagement & Assessment Design
Kiridena, S. B., Samaranayake, P., & Hastie, D. B. (2014)	Australia	Instructional Design for Online Course Delivery in Engineering Management: Synthesizing Learning Styles, Pedagogical Perspectives and Contingency Factors
Badurdeen, F., Baker, J. R., Rouch, K. E., Goble, C. F., Swan, G. M.,	United States	Development of an Online Master's Degree Program in Manufacturing Systems Engineering

Brown, A., & Jawahir, I. S. (2015)		
Minichiello, A., Legler, N., Hailey, C., & Adams, V. D. (2013)	United States	Online Engineering Course Design, Part I: Toward Asynchronous, Web-based Delivery of a First Course in Thermodynamics
Bozkurt, I., & Helm, J. (2013)	United States	Development and Application of a Systems Engineering Framework to Support Online Course Design and Delivery
Matzakos, N. M., & Kalogiannakis, M. (2018)	Greece	An analysis of first year engineering students' satisfaction with a support distance learning program in mathematic
de la Torre, L., Sàenz, J., Chaos, D., Sánchez, J., & Dormido, S. (2020)	Spain	A Master Course on Automatic Control Based on the Use of Online Labs
Batanero, C., de-Marcos, L., Holvikivi, J., Hilera, J. R., & Otón, S. (2019)	Spain	Effects of New Supportive Technologies for Blind and Deaf Engineering Students in Online Learning
Bir, D. D., & Ahn, B. (2017)	United States	Examining student attitudes to improve an undergraduate online engineering course
Danaher, M. (2014)	United Arab Emirates	Online Engineering Courses: Benchmarking Quality

Theme 2: Interactions in Online Engineering Courses

Authors	*Country affiliation of first author*	*Title*
Avanzato, R. L. (2017)	United States	Virtual World Technology to Support Student Collaboration in an Online Engineering Course
Fatehiboroujeni, S., Qattawi, A., & Goyal, S. (2019)	United States	Assessing and Improving Student Engagement and Motivation in Mechanical Engineering Online Courses
Yousuf, B., & Conlan, O. (2017)	Ireland	Supporting Student Engagement Through Explorable Visual Narratives
Odom, P. W., Merzdorf, H. E., Montalvo, F. J., & Davis, J. M. (2019)	United States	Analysis of Student Engagement Data from U.S. World News Report Regarding Online Graduate Engineering Programs
Fu, P. (2019)	United States	Trifecta of Engagement in an Online Engineering Management Course
Schutz, D. M., Kim, Y. Y., & Dionne, D. (2018)	Japan	Factors Influencing Student Veteran Participation in Online Engineering Education

Theme 3: Assessment in Online Engineering Courses

Authors	*Country affiliation of first author*	*Title*
Purwar, A., & Scott, C. A. (2019, June)	United States	An Online Engineering Dynamics Class for College Sophomores: Design, Implementation, and Assessment
Siddhpura, A., & Siddhpura, M. (2020, December)	Australia	Plagiarism, Contract Cheating And Other Academic Misconducts In Online Engineering Education: Analysis, Detection And Prevention Strategies
Pamplona, S., Seoane, I., & Bravo-Agapito, J. (2018, October)	Spain	Assessing Conceptual Knowledge in Three Online Engineering Courses: Theory of Computation and Compiler Construction, Operating Systems, and Signal and Systems
Balagiu, A., & Sandiuc, C. (2020)	Romania	Developing an online course for marine engineering
Chatterjee, R., Kamal, A. E., & Wang, Z. (2016, June)	United States	Alternate Assessments to Support Formative Evaluations in an Asynchronous Online Computer Engineering Graduate Course
Cooper, M. E., Bullard, L. G., Spencer, D., & Willis, C. (2020)	United States	Direct and Indirect Assessment of Student Perspectives and Performance in an Online/Distance Education Chemical Engineering Bridging Course Sequence
Fu, P. (2019)	United States	Trifecta of Engagement in an Online Engineering Management Course
Danaher, M. (2014)	United Arab Emirates	Online engineering courses: Benchmarking quality

Theme 4: Feedback in Online Engineering Courses

Authors	*Country affiliation of first author*	*Title*
Purwar, A., & Scott, C. A. (2019)	United States	An Online Engineering Dynamics Class for College Sophomores: Design, Implementation, and Assessment
Rutz, E., & Ehrlich, S. (2016)	United States	Increasing Learner Engagement in Online Learning through Use of Interactive Feedback: Results of a Pilot Study
Mansor, M. S. A., & Ismail, A. (2012)	Malaysia	Learning styles and perception of engineering students towards online learning
Fu, P. (2019)	United States	Trifecta of Engagement in an Online Engineering Management Course
Sancho-Vinuesa, T., Masià, R., Fuertes-Alpiste, M., & Molas-Castells, N. (2018)	Spain	Exploring the effectiveness of continuous activity with automatic feedback in online calculus

Theme 5: Challenges in Online Engineering

Authors	*Country affiliation of first author*	*Title*
Pedrosa, D., Morgado, L., Cravino, J., Fontes, M. M., Castelhano, M., Machado, C., & Curado, E. (2020)	Portugal	Challenges Implementing the SimProgramming Approach in Online Software Engineering Education for Promoting Self and Co-regulation of Learning
Perales Jarillo, M., Pedraza, L., Moreno Ger, P., & Bocos, E. (2019)	Spain	Challenges of Online Higher Education in the Face of the Sustainability Objectives of the United Nations: Carbon Footprint, Accessibility and Social Inclusion
Hachey, A. C., Wladis, C., & Conway, K. (2015)	United States	Prior online course experience and GPA as predictors of subsequent online STEM course outcomes
Cooper, M. E., Bullard, L. G., Spencer, D., & Willis, C. (2020)	United States	Direct and Indirect Assessment of Student Perspectives and Performance in an Online/Distance Education Chemical Engineering Bridging Course Sequence
Kiridena, S. B., Samaranayake, P., & Hastie, D. B. (2014)	Australia	Instructional Design for Online Course Delivery in Engineering Management: Synthesizing Learning Styles, Pedagogical Perspectives and Contingency Factors
Rutz, E., & Ehrlich, S. (2016)	United States	Increasing Learner Engagement in Online Learning through Use of Interactive Feedback: Results of a Pilot Study
Zhang, Y. (2020)	United States	A Cross-Referencing System for Curriculum Coordination in Multi-Institution Online Graduate Engineering Degree Programs: Case Study of the Virginia Engineering Online Program
Levy, Y., & Ramim, M. M. (2017)	United States	The E-Learning Skills Gap Study: Initial Results of Skills Desired for Persistence and Success in Online Engineering and Computing Courses
Hammout, N., & Hosseini, S. (2020)	Morocco	Involvement of students in online master’s studies of Engineering and Science: a path to minimize the gender gap in STEM

APPENDIX C

PERSISTER-BASED UNIQUE RULES

Persister-based unique rules

1. {F3_quiz.sub2_3=MED,F4_quiz.sub1_2=MED,F5_quiz.sub2=MED}=> {Persistence=Yes}
2. {F3_assignment.sub2_3=MED,F4_assignment.sub1_2=MED,F5_assignment.sub2 =MED}=>Persistence=Yes}
3. {F3_assignment.sub1_2=MED,F5_assignment.sub1=MED,F6_assignment.sub1=LOW}=>{Persistence=Yes}
4. {F1_quiz.sub2=MED,F2_quiz.sub2_3=MED,F6_quiz.sub2=LOW}=> {Persistence=Yes}
5. {F1_quiz2=MED,F1_quiz.sub2=MED,F6_quiz2=LOW} => {Persistence=Yes}
6. {F1_quiz.sub2=MED,F6_quiz2=LOW,F6_quiz.sub2=LOW}=>{Persistence=Yes}
7. {F1_quiz2=MED,F1_quiz.sub2=MED,F6_quiz.sub2=LOW}=>{Persistence=Yes}
8. {F1_assignment.sub3=MED,F6_assignment.sub1=LOW,F6_assignment.sub3=LOW}=> {Persistence=Yes}
9. {F1_quiz3=MED,F1_quiz.sub3=MED,F6_quiz3=LOW} => {Persistence=Yes}
10. {F1_quiz3=MED,F1_quiz.sub3=MED,F6_quiz.sub3=LOW}=>{Persistence=Yes}
11. {F1_quiz.sub3=MED,F6_quiz3=LOW,F6_quiz.sub3=LOW}=>{Persistence=Yes}
12. {F1_quiz.sub3=MED,F6_quiz1=LOW,F6_quiz.sub1=LOW}=>{Persistence=Yes}
13. {F1_quiz.sub3=MED,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=> {Persistence=Yes}
14. {F1_quiz.sub3=MED,F6_quiz.sub1=LOW,F6_quiz.sub3=LOW}=> {Persistence=Yes}

15. {F2_quiz1_2=MED,F2_quiz2_3=MED,F7_quiz123=MED} => {Persistence=Yes}

16. {F1_quiz2=MED,F2_quiz2_3=MED,F7_quiz123=MED} => {Persistence=Yes}

17. {F2_quiz2_3=MED,F6_quiz2=LOW,F6_quiz.sub2=LOW} => {Persistence=Yes}

18. {F1_quiz2=MED,F2_quiz2_3=MED,F6_quiz.sub2=LOW} => {Persistence=Yes}

19. {F1_quiz.sub1=MED,F2_quiz.sub1_2=MED,F6_quiz.sub1=LOW}=> {Persistence=Yes}

20. {F1_quiz1=MED,F2_quiz.sub1_2=MED,F6_quiz.sub1=LOW}=> {Persistence=Yes}

21. {F2_quiz.sub1_2=MED,F6_quiz1=LOW,F6_quiz.sub1=LOW}=> {Persistence=Yes}

22. {F6_quiz1=LOW,F6_quiz.sub1=LOW,F7_quiz123=MED} => {Persistence=Yes}

23. {F1_quiz1=MED,F1_quiz.sub1=MED,F6_quiz1=LOW} => {Persistence=Yes}

24. {F1_quiz1=MED,F1_quiz.sub1=MED,F6_quiz.sub1=LOW}=>{Persistence=Yes}

25. {F1_quiz.sub1=MED,F6_quiz1=LOW,F6_quiz.sub1=LOW}=>{Persistence=Yes}

26. {F1_quiz.sub1=MED,F6_quiz.sub1=LOW,F6_quiz.sub3=LOW}=> {Persistence=Yes}

27. {F1_quiz.sub1=MED,F6_quiz.sub1=LOW,F6_assignment.sub1=LOW}=> {Persistence=Yes}

28. {F2_quiz1_2=MED,F6_quiz2=LOW,F6_quiz.sub2=LOW} => {Persistence=Yes}

29. {F1_quiz1=MED,F1_quiz2=MED,F2_quiz1_2=MED} => {Persistence=Yes}

30. {F1_quiz1=MED,F2_quiz1_2=MED,F6_quiz1=LOW} => {Persistence=Yes}

31. {F1_quiz1=MED,F2_quiz1_2=MED,F6_quiz.sub1=LOW} => {Persistence=Yes}

32. {F1_quiz2=MED,F2_quiz1_2=MED,F6_quiz.sub2=LOW} => {Persistence=Yes}

33. {F2_quiz1_2=MED,F6_quiz1=LOW,F6_quiz.sub1=LOW} => {Persistence=Yes}

34. {F3_assignment.sub2_3=MED,F4_assignment.sub1_2=MED,F6_assignment.sub2 =LOW} => {Persistence=Yes}

35. {F1_quiz3=MED,F6_quiz.sub1=LOW,F6_quiz3=LOW} => {Persistence=Yes}

36. {F1_quiz3=MED,F6_quiz1=LOW,F6_quiz.sub3=LOW} => {Persistence=Yes}

37. {F1_quiz3=MED,F6_quiz1=LOW,F6_quiz.sub1=LOW} => {Persistence=Yes}

38. {F1_quiz3=MED,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=> {Persistence=Yes}

39. {F1_quiz3=MED,F6_quiz.sub1=LOW,F6_quiz.sub3=LOW}=>{Persistence=Yes}

40. {F1_quiz2=MED,F6_quiz2=LOW,F6_quiz.sub2=LOW} => {Persistence=Yes}

41. {F6_quiz.sub1=LOW,F6_quiz2=LOW,F6_quiz.sub2=LOW}=>{Persistence=Yes}

42. {F1_quiz1=MED,F6_quiz3=LOW,F6_quiz.sub3=LOW} => {Persistence=Yes}

43. {F1_quiz1=MED,F6_quiz1=LOW,F6_quiz.sub3=LOW} => {Persistence=Yes}

44. {F1_quiz1=MED,F6_quiz1=LOW,F6_quiz.sub1=LOW} => {Persistence=Yes}

45. {F1_quiz1=MED,F6_quiz.sub1=LOW,F6_quiz.sub3=LOW}=>{Persistence=Yes}

46. {F1_quiz1=MED,F6_quiz.sub1=LOW,F6_assignment.sub1=LOW}=> {Persistence=Yes}

47. {F1_quiz2=MED,F6_quiz.sub2=LOW,F6_assignment.sub2=LOW}=> {Persistence=Yes}

48. {F6_quiz1=LOW,F6_quiz.sub1=LOW,F6_quiz.sub2=LOW}=>{Persistence=Yes}

APPENDIX D

LEAVER-BASED UNIQUE RULES

Leaver-based unique rules

1. {F6_assignment.sub1=LOW,F6_assignment.sub3=LOW,F8_assignment.sub123=LOW}=> {Persistence=No}
2. {F6_quiz3=LOW,F6_canvas3=LOW,F6_quiz.sub3=LOW} => {Persistence=No}
3. {F6_quiz3=LOW,F6_canvas3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
4. {F6_canvas3=LOW,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
5. {F6_quiz3=LOW,F6_grades3=LOW,F6_quiz.sub3=LOW} => {Persistence=No}
6. {F6_quiz3=LOW,F6_grades3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
7. {F6_grades3=LOW,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
8. {F6_quiz3=LOW,F6_wiki3=LOW,F6_quiz.sub3=LOW} => {Persistence=No}
9. {F6_quiz3=LOW,F6_wiki3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
10. {F6_wiki3=LOW,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
11. {F4_assignment.sub2_3=MED,F5_assignment.sub3=MED,F6_assignment.sub3=LOW}=> {Persistence=No}
12. {F6_quiz3=LOW,F6_assignment3=LOW,F6_quiz.sub3=LOW}=> {Persistence=No}

13. {F6_quiz3=LOW,F6_assignment3=LOW,F6_assignment.sub3=LOW}=>
{Persistence=No}
14. {F6_assignment.sub1=LOW,F6_assignment3=LOW,F6_quiz.sub3=LOW}=>
{Persistence=No}
15. {F6_assignment.sub1=LOW,F6_assignment3=LOW,F6_assignment.sub3=LOW}
=> {Persistence=No}
16. {F6_assignment3=LOW,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=>
{Persistence=No}
17. {F6_quiz3=LOW,F6_attach3=LOW,F6_quiz.sub3=LOW} => {Persistence=No}
18. {F6_quiz3=LOW,F6_attach3=LOW,F6_assignment.sub3=LOW}=>
{Persistence=No}
19. {F6_assignment.sub1=LOW,F6_attach3=LOW,F6_assignment.sub3=LOW}=>
{Persistence=No}
20. {F6_attach3=LOW,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=>
{Persistence=No}
21. {F6_quiz2=LOW,F6_quiz.sub2=LOW,F6_assignment.sub3=LOW}=>
{Persistence=No}
22. {F6_quiz.sub3=LOW,F6_assignment.sub3=LOW,F7_grades123=MED}=>
{Persistence=No}
23. {F6_quiz1=LOW,F6_quiz3=LOW,F6_assignment.sub3=LOW}=>
{Persistence=No}

24. {F6_quiz1=LOW,F6_assignment.sub1=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
25. {F3_assignment.sub1_2=MED,F6_quiz3=LOW,F6_quiz.sub3=LOW}=> {Persistence=No}
26. {F3_assignment.sub1_2=MED,F6_assignment.sub1=LOW,F6_assignment.sub3= LOW}=> {Persistence=No}
27. {F3_assignment.sub1_2=MED,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW} => {Persistence=No}
28. {F6_quiz.sub1=LOW,F6_assignment.sub1=LOW,F6_quiz3=LOW}=> {Persistence=No}
29. {F6_quiz.sub1=LOW,F6_quiz3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
30. {F6_quiz.sub2=LOW,F6_quiz3=LOW,F6_quiz.sub3=LOW}=>{Persistence=No}
31. {F6_quiz.sub2=LOW,F6_assignment.sub2=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
32. {F6_quiz.sub2=LOW,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}
33. {F4_assignment.sub2_3=MED,F6_quiz3=LOW,F6_quiz.sub3=LOW}=> {Persistence=No}
34. {F4_assignment.sub2_3=MED,F6_quiz3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}

35. {F4_assignment.sub2_3=MED,F6_assignment.sub1=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}

36. {F6_assignment.sub2=LOW,F6_quiz3=LOW,F6_quiz.sub3=LOW}=> {Persistence=No}

37. {F6_assignment.sub1=LOW,F6_quiz3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}

38. {F6_assignment.sub2=LOW,F6_quiz.sub3=LOW,F6_assignment.sub3=LOW}=> {Persistence=No}

APPENDIX E

PROCESSES

E1. Preparing Data Required to Conduct ARM

1. Use the cleaned data to create natural features representing,
    a. the time students spent on various course aspects, and
    b. how these times change across the duration of the course.
2. Derive relative features using the natural features.
3. Use the feature selection part of the random forest algorithm to identify features that uniquely distinguish completers and leavers.
4. Use random forest algorithm's output (Gini index) to eliminate the relative features whose contribution is the least (or nil/negligible).
5. Use SMOTE to up-sample the data as desired (in this study the following ratios of leavers to completers were used 1:1.09, 1:2, 1:3, 1:4, 1:5, 1:6, 1:7, and 1:9).
6. Arrange the data in the format required to conduct ARM,
    a. each column representing a relative feature ($F = \{f_1, f_2, f_3, \ldots, f_Z\}$, up to Z-number of relative features),
    b. last column including the persistence variable (Yes=completers, No=leavers),
    c. each row representing a different student.

E2. Conducting Association Rule Mining

1. Use quartiles to discretize the data into three bins as LOW ($\leq Q_1$), MED ($>Q_1$ and $\leq Q_3$), and HIGH ($>Q_3$) student engagement relative to the average student in the class.

2. Set minimum and maximum rule length and then finalize the values for support and confidence by varying the desired number of rules to be generated (we generated rules starting from 20 up to 70 in incremental steps of 5).
3. Run the *a priori* ARM algorithm for completers and leavers separately.
4. Sort the rules generated by the algorithm.
5. Prune the rules to avoid rules that are subset of the other rules.
6. Identify unique rules by comparing completers- and leavers-based rules (some rules appearing in completer- and leaver-based rules might be the same)

E3. Computing Student Engagement Score Using the Rules

1. Decide the various candidate engagement scores and sampling ratio to compute the final student engagement score.
2. Compute the student engagement score using each candidate engagement score and each sampling ratio of leavers to completers.
3. Apply logistic regression on each candidate engagement score for each sampling ratio separately.
4. Use the confusion matrix from the logistic regression output to compute the performance measures (sensitivity, specificity, accuracy rate, precision rate, error rate, and AUC).
5. Analyze the performance measures to select the candidate for computing the final engagement score (in our study, [X-Y] was chosen).

APPENDIX F

SURVEY INSTRUMENTS

Survey Instruments

Note: All items were asked on a five-point Likert scale, from 1=Strongly disagree to 5=Strongly Agree

1. Course Characteristics

Perceptions of the LMS (Dialogue)

Definition: How comfortable the student feels using the course Canvas site to communicate with the course (i.e., the instructor and other students).	
1	I feel comfortable using the course Canvas site to converse with others.
2	I feel comfortable using the course Canvas site to communicate with the instructor.
3	I feel comfortable using the course Canvas site to ask questions to others.
4	I feel comfortable using the course Canvas site to initiate conversation with other students.
5	I feel comfortable using the course Canvas site to participate in online course discussions.

Perceptions of the LMS (Course-Technology Fit)

Definition: How satisfied the student feels with the way the instructor uses the course Canvas site to support student learning	
1	Overall, I am satisfied with the technology used.
2	I am satisfied with the format of the material provided.
3	I am satisfied with the resources provided (e.g., links, materials, resources) to support learning.
4	I am satisfied with the way that content is delivered.
5	I am satisfied with the mechanisms through which assessments are delivered.

Perceptions of the LMS (Ease of Use)

Definition: How easy the student feels it is to navigate the course Canvas site	
1	The course Canvas site is easy to use.
2	It is easy to get my work done using the course Canvas site.
3	It is easy to submit an assignment through the course Canvas site.
4	It is easy to access content within the course Canvas site.
5	It is easy to view my current grade in the course within the course Canvas site.

Perceptions of Instructor Practices (Instructional Style)

Definition: How well the instructor utilizes diverse teaching practices to get students involved and engaged in the course	
1	The instructor incorporates a variety of different approaches to learning.
2	The instructor helps to keep students engaged.
3	The instructor encourages students to work with peers.
4	The instructor delivers course content in a way that keeps things exciting.
5	The instructor provides a variety of information sources related to relevant issues.

Perceptions of Instructor Practices (Rapport)

Definition: Student perceptions of the quality of the student-instructor relationship	
1	The instructor welcomes questions from students.
2	The instructor has a caring demeanor.
3	The instructor shows enthusiasm about student success.
4	The instructor solicits student ideas and feedback about the course.
5	The instructor makes it clear that students may contact them at any time.
6	The instructor has made an effort to get to know me as an individual.

Perceptions of Instructor Practices (Feedback and Evaluation)

Definition: Student perceptions of the quality of instructor feedback and evaluation	
1	The instructor provides helpful feedback.
2	The instructor provides feedback in a timely fashion.
3	The instructor provides multiple opportunities for students to check their current performance.
4	The instructor provides suggestions for how to prepare for assessments.
5	The instructor provides students with ample opportunities to do graded work.

Perceptions of Instructor Practices (Content)

Definition: Student perceptions of the quality of the instructor's approach for presenting course content	
1	The instructor explains concepts in a way that makes them easy to understand.
2	The instructor seems knowledgeable about course material.
3	The instructor presents material at an appropriate level of difficulty.
4	The instructor gives helpful examples to support class concepts.
5	The instructor presents course material in ways that build on my prior knowledge.
6	The instructor talks about ways course material can be applied in the real world.

Perception of Instructor Practices (Course Management)

Definition: Student perception of the quality of the instructor's course management practices	
1	The instructor clearly communicates course goals and expectations.
2	The instructor gives assignments that align with course goals.
3	The instructor clearly communicates the importance of course topics.
4	The instructor presents course content that is consistent with the syllabus.
5	The instructor abides by the course schedule.

Perceptions of Peer Support

Definition: The extent to which the student feels both instrumental and emotional support from other students in the course	
1	I have access to peer support in this course.
2	I have been able to get to know other students in the course.
3	I can ask questions of other students in the course.
4	I can join study groups with other students in the course if I want to.
5	I am connected to other students in the course.
6	I am part of a community in this course.

2. Expectancies and Values

Expectancies of Success

Definition: How confident the student feels in their ability to complete the course	
1	I can complete the assignments for this course.
2	I can successfully pass this course.
3	I can satisfy the objectives for this course.
4	I can meet the expectations set out for me in this course.
5	I can master the knowledge and skills taught in this course.

Subjective Task Values (Intrinsic Value)

Definition: How much enjoyment the student perceives from engaging in course activities	
1	I like taking this course.
2	I am very interested in the content of this course.
3	I find the material covered in this course exciting.
4	I enjoy learning about the topics covered in this course.
5	Working on assignments for this course is fun for me.

Subjective Task Values (Utility Value)

Definition: How much utility the student perceives in the course for their future goals	
1	What I am learning in this course will be useful for my career.
2	The material I am learning in this class is relevant to my life.
3	Taking this course will help me achieve my professional goals.
4	I will learn a lot of useful skills by taking this course.
5	The content I am learning in this course will help me succeed in future courses.

Subjective Task Values (Attainment Value)

Definition: How much importance the student places on successfully completing the course	
1	Taking this course is important to me.
2	The amount of effort it might take to do well in this course is worthwhile to me.
3	Mastering the knowledge and skills taught in this class is important to me.
4	I will be proud of myself if I complete this course.
5	Completing this course will make me feel good about myself.
6	It is important to me that I finish this course.

Ability Self-Concept

Definition: The extent to which students believe they can complete the course	
1	I am capable of completing this course.
2	I can perform the tasks required in this course.
3	I can overcome difficulties I encounter this course.
4	I can be successful in this course.
5	This course is easy for me.

Course Difficulty

Definition: The perceived level of difficulty in completing tasks required in the course	
1	I find that this course is difficult.
2	I find the tasks required in this course to be hard.
3	The tasks required in this course are challenging to me.
4	This course is more difficult than I expected.
5	The content presented in this course is hard to understand.

3. Intentions to Persist

Definition: Student's perception of their intention to successfully complete the course with a passing grade	
1	I intend to complete this course.
2	I am not thinking about dropping from this course.
3	I am fully committed to completing this course.
4	I do not see any reasons to withdraw from this course.
5	I plan to still be enrolled in the course next week.

4. Daily General Mood

Definition: The students' general mood at the time of taking each survey.	
1	Overall, how are you feeling today?

5. Background Characteristics and Previous Academic Achievement

As part of an initial screening survey

The Online Engineering Student Questionnaire	
Consent	1. Ready to go? Please read the form below and confirm your consent to participate by DATE. 2. I have read the text above, I am 18 years of age or older, and I agree to participate in this survey. 1. Yes 2. No
Section 1: Current Degree and Course Enrollment	
1. Student placement within the program	What is your current class standing? 1. Freshmen 2. Sophomore 3. Junior 4. Senior 5. Fifth year senior 6. Other, please specify
2. Degree fields	What degree field are you currently pursuing? 1. Electrical Engineering 2. Engineering Management 3. Software Engineering 4. Others, please specify

3. Degree types	What degree type are you currently pursuing? 1. BSE 2. MSE 3. MBA/ MSE
4. Expected graduation date	When is your expected graduation date? [a drop-down in next ten years] and beyond that (2029 or later)
5. Total credits student is taking this session	How many credits do you plan to take during this current session? [a drop-down option] 1. 0 2. 1-3 3. 4-6 4. 7-9 5. More than 9
6. Online course	Please select the online courses in which you are currently enrolled (Mark all that apply.) 1. Course title 1 2. Course title 2 3. Course title 3 4. Course title 4
7. Previous online learning experience	Have you taken online courses previously? 1. Yes 2. No [If, yes] Please select the number of online courses you've completed prior to this session. 1. 1-2 2. 3-4 3. 5-6 4. 7-8 5. More than 9
Section 2: Background Information	
8. Gender	What is your current gender identity? 1. Male 2. Female 3. Trans male/ Trans Man 4. Trans female/ Trans woman 5. Genderqueer/ Gender Non-conforming 6. Prefer to self-describe, please specify: 7. Prefer not to say

9. Age	What is your current age? [a scroll down option from 18 to 65 or older]
10. Citizenship status	What is your residency status? 1. US citizen 2. Permanent Resident (e.g., green card holder) 3. Student visa holder 4. Others, please specify:
11. Race/ Ethnicity	How would you describe your race/ethnicity? Please select all that apply. 1. American Indian or Alaska native 2. Asian 3. Black or African American 4. Hispanic or LatinX 5. Native Hawaiian or Other Pacific Islander 6. White
12. First-generation	Have any of your parents or legal guardians attended college for a bachelor's or associate's degree (whether or not they completed the degree)? 1. Yes 2. No
13. Transfer student	Are you: 1. A transfer student from a two-year institution 2. A transfer student from a four-year institution 2. Neither
14. Veteran	Are you a veteran of the U.S. Armed Forces? 1. Yes 2. No
15. Relationship status	What best describes your relationship status? 1. Single/ Never married 2. Separated, Divorced, or Widowed 3. Married 4. In a committed relationship
16. Working obligations	What is your current employment status? 1. Working full-time 2. Working part-time 3. Not working [If 1 or 2 selected] How many hours per week do you currently work? 1. 0-5 hours

	2. 6-10 hours 3. 11-15 hours 4. 15-20 hours 5. 25-30 hours 6. 30-35 hours 7. 35-40 hours 8. More than 40 hours
17. Family responsibilities	16. Do you have dependent children? 1. Yes 2. No [If, yes] Which of the statements below best describe your responsibilities? 1. I am the primary caregiver for a dependent child/ children 2. I am not the primary caregiver for a dependent child/ children 3. I equally share the care of a dependent child/ children
18. (GPA average)	What is your overall college grade GPA on a 4.00 scale? 1. 4.00 or above (A or higher) 2. 3.67-3.99 (A-) 3. 3.33-3.66 (B+) 4. 3.00-3.32 (B) 5. 2.67-2.99 (B-) 6. 2.33-2.66 (C+) 7. 2.00-2.32 (C) 8. 1.99 or below (C or lower)
19. Time and study management	Please indicate how true of the following statement are to you. (5-point Likert-type scale, from 1 (never of rarely true of me) to (Always or almost always true of me) 1. I usually study where I can concentrate on my course work. 2. I make good use of my study time in my courses. 3. I find it hard to stick to a study schedule. (Reverse) 4. I have a regular place set aside for studying. 5. I make sure I keep up with the weekly readings and assignments for my courses. 6. I often don't spend enough time on my courses because of other activities. (Reverse)
Longitudinal Study Sign Up	
	1. Name 2. Email address 3. Cell phone no.

APPENDIX G

IRB DOCUMENTS

IRB APPROVAL LETTER

ASU Knowledge Enterprise Development

EXEMPTION GRANTED

Samantha Brunhaver
IAFSE-PS: Polytechnic Engineering Programs (EGR)
480/727-1883
Samantha.Brunhaver@asu.edu

Dear Samantha Brunhaver:

On 6/15/2019 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	Staying the course: Understanding the motivational factors contributing to persistence among undergraduate engineering students in online courses.
Investigator:	Samantha Brunhaver
IRB ID:	STUDY00010303
Funding:	Name: National Science Foundation (NSF), Grant Office ID: FP00014302, Funding Source ID: 1825732
Grant Title:	FP00014302;
Grant ID:	FP00014302;
Documents Reviewed:	• Eligibility letter (Eligible participant), Category: Recruitment Materials; • Survey (including screening/ background survey), Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Consent form, Category: Consent Form; • IRB application, Category: IRB Protocol; • Recruitment letter, Category: Recruitment Materials; • SMS message (for SMS messaging survey), Category: Recruitment materials/advertisements /verbal scripts/phone scripts; • Eligibility letter (Ineligible participant), Category: Recruitment Materials; • Online Persistence Study Proposal 2018, Category: Sponsor Attachment;

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (1) Educational settings on 6/15/2019.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Sincerely,

IRB Administrator

cc: Jennifer Bekki
Eunsil Lee
Javeed Kittur
Samantha Brunhaver

RECRUITMENT EMAIL

Subject: Invitation to Help Improve the ASU Online Engineering Experience

Dear Student,

We are a team of investigators in the Ira A. Fulton Schools of Engineering at ASU. We are conducting a National Science Foundation-funded research project focused on understanding online undergraduate engineering education. As a current undergraduate student in an online engineering program at ASU, you are invited to participate.

Participation includes submission of a brief demographic survey and (if eligible) completion of a series of longitudinal surveys to be distributed 2 times per week for 6 weeks over the upcoming academic term. Each survey should take about 10 minutes to complete and will ask questions about a particular online engineering course in which you are enrolled. Surveys will be delivered via SMS message. All participants will receive a $5 Amazon gift card for completing one survey, or $15 Amazon gift card for completing both surveys (for a maximum of $90 for full participation over the course of the study) as compensation for their time.

If you are interested in participating, please fill out the demographic survey at the link below by xx/xx. A member of the research team will contact you within 1 week about your eligibility to participate in the study. will start in two weeks, at the beginning of the upcoming academic term.

To participate, please follow this link to the survey:
https://xxxxxxxxxxxxxxxx

Or copy and paste the URL below into a web browser:
https://xxxxxxxxxxxxxxxx

This study has been approved by the ASU Institutional Review Board (protocol number: STUDY########). For questions or further information regarding this research, please feel free to contact the research team at [online.engineering.study@gmail.com].

Sincerely,

Samantha Brunhaver, Assistant Professor
Jennifer Bekki, Associate Professor
Ira A. Fulton Schools of Engineering
Arizona State University

ASU Ira A. Fulton Schools of Engineering

ELIGIBILITY EMAIL

Subject: Welcome to the Online Undergraduate Engineering Education Study

Dear [Student Name],

Thank you for your interest in participating in the NSF-funded Online Undergraduate Engineering Education Study to better understand students' experiences related to online engineering education at ASU. Based on the responses to your initial demographic survey, we are pleased to let you know that you have been selected for participation.

Correspondingly, we'd like to ask that you carefully read and follow the instructions below. **These includes detailed information about the procedures, compensation, and requirements surrounding your participation.**

Participant Instructions

1. ***Designated course for your participation:*** In this study, a specific online course is designated for each participant so that we can track your experiences in that course over the duration of the study. [Course number] is the designated course for your participation in this study. While you may be enrolled in other online course, please keep in mind your experiences in [Course number] specifically as you respond to each survey. We will be periodically reminding you of this number throughout each survey as well.

2. ***SMS messaging survey:*** You will receive an SMS message with a URL when it is time to take each new survey. The SMS message will look as it is shown in the picture below. Click on the link and you will be directed to the survey. You can also respond to the survey with "STOP" to opt yourself out of the study at any time.

3. ***Survey schedule:*** New surveys will be sent to you at [9:00 am] on the dates shown below. Please respond to the survey within 36 hours of receiving the SMS message; otherwise, the link to the survey will expire and you will not be able to take that particular survey.

   Week 1: Thursday, January 23 and Monday, January 27

   Week 2: Thursday, January 30 and Monday, February 3

   Week 3: Thursday, February 6 and Monday, February 10

   Week 4: Thursday, February 13 and Monday, February 17

   Week 5: Thursday, February 20 and Monday, February 24

   Week 6: Thursday, February 27 and Monday, March 2

4. ***Mobile number:*** New surveys will be sent to you at the mobile phone number you designated in your initial demographic survey: **[XXX-XXX-XXXX]**. If you see any errors in how your phone number appears, please don't hesitate to contact the research team at [online.engineering.study@gmail.com].

5. ***Compensation:*** You will be compensated with a **$5 Amazon gift card** for completing one survey, or **$15 Amazon gift card** for completing both surveys ($90 for full participation over the course of the study). Every week that you are participatory, you will receive an email with the gift card codes of the cards you earned that week ($5 or $15, depending on your level of participation). **Please be sure to acknowledge receipt of the gift card by responding to the email, as this is important for institutional reporting purposes.**

6. ***Survey participation:*** You will be considered non-participatory if you miss two consecutive surveys, so **please be active survey participants!** You will receive compensation for any surveys completed up to the point your participation is discontinued. Please note that there may also be circumstances under which the investigators determine that you should not continue in the research.

Thank you again for your time and contribution to this important effort, and please feel free to contact the research team at [online.engineering.study@gmail.com] with any questions or concerns. We look forward to conducting this research with you!

Sincerely,

Samantha Brunhaver, Assistant Professor
Jennifer Bekki, Associate Professor
Ira A. Fulton Schools of Engineering
Arizona State University

Ira A. Fulton Schools of Engineering

INELIGIBLE EMAIL

Subject: Eligibility Status – Online Undergraduate Engineering Education Study

Dear [Student Name],

Thank you for your interest in participating in the NSF-funded study to better understand students' experiences related to online engineering education at ASU. Based on the responses to your initial demographic survey, we are sorry to inform you that you are not eligible for participation in the study at this time. Your survey responses and contact information will be immediately deleted, and no response from your end is required.

Thank you again for your interest in our study; we hope you will look out for future opportunities to participate!

Sincerely,

Samantha Brunhaver, Assistant Professor
Jennifer Bekki, Associate Professor
Ira A. Fulton Schools of Engineering
Arizona State University

ASU Ira A. Fulton Schools of Engineering

CONSENT FORM

Arizona State University

Informed Consent for Participants

STUDY TITLE: Staying the course: Understanding the motivational factors contributing to persistence among undergraduate engineering students in online courses.

INVESTIGATORS:
Dr. Samantha Brunhaver, Assistant Professor
Dr. Jennifer Bekki, Associate Professor

STUDY PURPOSE: The aim of this study is to better understand the experiences of undergraduate engineering students enrolled in online courses at ASU. You are invited to participate in this research study because you are at least 18 years of age and are currently enrolled in an online undergraduate engineering degree program at ASU. We expect about 200 people to participate in this study.

PROCEDURES: If you agree to be in this research, your participation will take place in two parts. First, you will be asked to complete a brief (~10 minute) online demographic survey. A member of the research team will contact you within 1 week of your submission about your eligibility to participate in the second, longitudinal part of the study based on your responses. If you are eligible, you will receive 2 surveys per week for 6 weeks coinciding with the upcoming academic term. Each survey will last no more than 10 minutes and will ask questions about a particular course in which you are enrolled. Surveys will be delivered to your mobile phone via SMS message between [Date of first survey] and [Date of last survey]. The anticipated total time for your complete participation is 120 minutes. If you are not eligible to participate in the longitudinal part of the study, you will be notified, and your demographic survey and contact information will immediately be deleted.

COMPENSATION: Participants will receive a $5 Amazon gift card for completing one of the two surveys, or a $15 Amazon gift card for completing both surveys ($90 for full participation over the course of study) as compensation for their time; gift cards will be disbursed once per week.

RISKS: There are no significant risks associated with your participation

BENEFITS: Participation will provide valuable information that may help university faculty and administrators improve the quality of the online engineering education offered by ASU. You may also benefit from the opportunity to reflect on your learning and experiences in your online course throughout the study.

ANONYMITY & CONFIDENTIALITY: Participation in this study is completely confidential. Results from this study will be published, only in aggregate, in journal and conference papers. All data (including your demographic information, phone number, and survey responses) will be stored electronically on password-protected computers and ASU cloud storage. The principal investigators and a team of authorized graduate students will be the only people who have access to the data. A list of participants and their contact information will be kept during the study for the purposes of collecting the longitudinal data from them. This list will be accessible by the research team only and will be destroyed at the conclusion of data collection. You will be assigned a random ID code after data collection and prior to data analysis. All sources of data collected from you will be linked by this ID code, and data analysis will be conducted with this de-identified data only.

FREEDOM TO WITHDRAW: You are free to withdraw from this study at any time, and it will not be held against you. You are free to choose to respond to any question without penalty. You will receive compensation for any surveys completed up to the point you end your participation. Please note that there may also be circumstances under which the investigators determine that a participant should not continue in the research.

QUESTIONS OR CONCERNS: If you have questions about this research, please contact one of study investigators: Dr. Samantha Brunhaver (Samantha.Brunhaver@asu.edu) or Dr. Jennifer Bekki (Jennifer.Bekki@asu.edu). If you have any questions about your rights as a participant in this research, or if you feel you have been placed at risk, you can contact the Arizona State University Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788 or Research.Integrity@asu.edu.

I have read the CONSENT FORM above and agree with all the terms and conditions, specifically my participation in this two-part study. I provide my consent for the investigators to use my information for research purposes in the study and acknowledge that I am 18 years or older.

- Yes