



# Role of Course and Individual Characteristics in the Course-level Persistence Intentions of Online Undergraduate Engineering Students: A Path Analysis

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## ABSTRACT

Online learning is increasing in both enrollment and importance within engineering education. Online courses also continue to confront comparatively higher course dropout levels than face-to-face courses. This research paper thus aims to better understand the factors that contribute to students' choices to remain in or drop out of their online undergraduate engineering courses. Path analysis was used to examine the impact of course perceptions and individual characteristics on students' course-level persistence intentions. Specifically, whether students' course perceptions influenced their persistence intentions directly or indirectly, through their expectancies of course success, was tested.

Data for this study were collected from three ABET-accredited online undergraduate engineering programs at a large public university in the Southwestern United States: electrical engineering, engineering management, and software engineering. A total of 138 students participated in the study during the fall 2019 (n=85) and spring 2020 (n=53) semesters. Participants responded to surveys twice weekly during their 7.5-week online course. The survey asked students about their course perceptions related to instructor practices, peer support, and course difficulty level, their expectancies in completing the course, and their course persistence intentions. This work is part of a larger National Science Foundation-funded research project dedicated to studying online student course-level persistence based on both students' self-report data and course learning management system (LMS) activity.

The survey sample was consistent with reports indicating that online learners tend to be more diverse than face-to-face learners. Findings from the path analysis revealed that students' perceptions of course LMS fit, perceived course difficulty, and expectancies of course success positively and significantly predicted persistence intentions, making them the most important influences. Expectancies of course success had a direct effect on persistence intentions. The findings underscore needs to elucidate further the mechanisms through which expectancies of success influence persistence.

## KEYWORDS

Online learning, course perceptions, persistence

## Introduction

Online education offers numerous advantages such as accessibility, flexibility, and scalability (Rovai, and Downey, 2010). For these reasons, it continues to gain widespread recognition and acceptance as evident from the rising number of student enrollments over the last decade (Seaman, Allen, and Seaman, 2018). Yet, despite the advantages online education offers, it has been known for its higher dropout rates compared to in-person instruction (Frydenberg, 2007; Heyman, 2010). While engineering education has been slower in comprehensively adopting the online format of education relative to other fields, the number of online engineering courses and degree programs has been growing (ABET, Inc., 2021), and research

on online engineering education is specifically lacking. Therefore, student persistence in online engineering education remains an issue that needs to be addressed.

The work presented in this study is part of a larger National Science Foundation (NSF) funded research study aimed at building a theoretical model for student persistence in online undergraduate engineering courses (Brunhaver et al., 2019). The Model for Online Course-Level Persistence in Engineering (MOCPE) framework used in this project is shown in Figure 1, and it includes both course and individual characteristics (Lee et al., 2020). This study investigates a subset of the model to better understand the individual and course characteristics that contribute to students' choices to remain in or drop out of their online undergraduate engineering courses. Specifically, we use path analysis to examine how students' course perceptions and expectancies of course success impact their course-level persistence intentions. We also test whether students' course perceptions related to their instructor, peers, and learning management system (LMS) influence their persistence intentions directly or indirectly, through expectancies of course success.

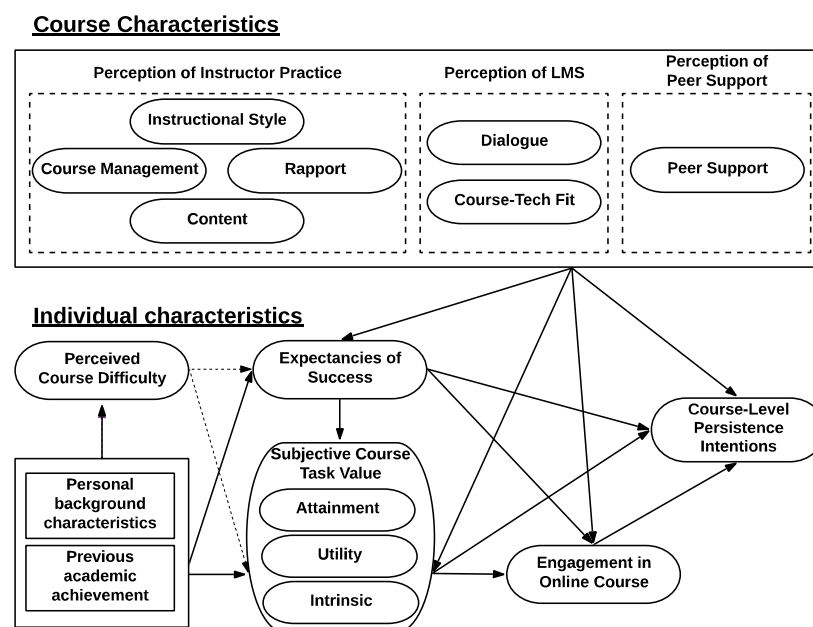


Figure 1: Model for Online Course-Level Persistence in Engineering (MOCPE) (Lee et al., 2020)

## Course and Individual Characteristics in Online Courses

Due to their remote format, online courses have shown to increase boredom, isolation, and frustration among students (Young, 2006). The interpersonal interactions that take place between student-to-student and student-to-instructor in online courses can significantly mitigate these effects and enhance the quality of students' experience (Moore, 1993; York and Richardson, 2012). Interpersonal interactions help connect students to their teachers and classmates, enhancing numerous positive student outcomes (Luo, Zhang, and Qi, 2017; Muir, Douglas, and Trimble, 2020). For example, in one study, instructor online presence and connection with the instructor significantly improved student learning (Martin, Wang, and Sadaf, 2018). In another study, instructor presence and behavior in online courses was reported to influence student engagement (Muir et al., 2019).

Like instructor support, peer support has shown to benefit online students. Peer interactions in online courses are beneficial in exchanging knowledge and collaborating on projects, activities which in turn help build connections with other students and enhance sense of belonging (Luo, Zhang, and Qi, 2017; Muir, Douglas, and Trimble, 2020). Both instructor and peer support have

also been linked to online student persistence decisions. Hart (2012) confirmed peer support as a top influencer on students' decisions to complete or withdraw from their online courses, while the absence of peer interactions negatively impacted students' persistence decisions in Robertson (2020). Notably, learner-to-learner and learner-to-instructor interactions were used in another study to identify students at risk of dropping in online courses; researchers identified the quality of online interactions with others to be a significantly better indicator than amount of interaction in student success and persistence (Shelton, Hung, and Lowenthal, 2017).

Researchers have also used students' individual characteristics to study their persistence decisions in online courses. In their review study of online course droppers, Lee and Choi (2011) reported that students with higher levels of self-motivation, internal locus of control, confidence in computer skills, and course self-efficacy were more likely to persist in and complete the courses. In another study, Yang et al. (2017) investigated the persistence factors of fully online students and identified mastery of specific skills and perceived utility of learning among the top two influences. Willging and Johnson (2009) reported four reasons why students leave online programs: personal reasons (financial difficulties, time management, family problems), job-related reasons (lack of employer support, difficulty in managing work and student responsibilities, changing job responsibilities), program-related reasons (difficult program, too many assignments, lack of interactions with students and instructor), and technology-related reasons (de-personalized learning environment, lack of support from the staff). Other work has found prior academic achievement and continuous academic enrollment to be helpful (Salvo et al., 2019).

Perceptions of the online course learning management system, course difficulty, and expectancies of course success have been a critical aspect in influencing students' persistence decision in online courses. For example, Bunn (2004) in a study on student persistence in distance education reported access to resources and coursework issues as barriers to distance learning. Difficulty in accessing course related materials was cited as reasons for students to drop out of online courses in several other studies (Hart, 2012; St Rose and Moore, 2019). Students are likely to not perform well or discontinue a course if they find the course difficult. Robertson (2020) reported that challenges and frustrations related to the discussion board in online courses as one of the factors influencing student's decision to drop out. Confidence in one's abilities of performing the course related tasks is likely to help them persist and successfully complete the course. Lee and Choi (2011) in a review study on online course dropouts argued that students with internal locus of control, higher levels of self-efficacy, satisfaction with courses, and self-motivation were more likely to complete the course.

In this paper we focus on the subset of the MOCPE model i.e., we examine the relationships between course perceptions, expectancies of course success, and course-level persistence intentions. Expectancies of course success among other variables influences a student's engagement and motivation to persist (Wigfield and Eccles, 2000), hence, expectancies of course success is hypothesized to mediate the relationship between course perceptions and course-level persistence intentions.

## Methods

### Participants

Participants for this study were enrolled in one of three ABET-accredited online undergraduate engineering programs (electrical engineering, engineering management, software engineering) at a large, public university in the Southwestern United States. A total of 138 participants were recruited (85 during fall 2019 and 53 during early spring 2020 before the pandemic). Participants were 23% women, 82% transfer students, 33% first-generation college students, and 28% U.S. military veterans. Their race/ethnicities included White (73%), Asian (3%), Hispanic/LatinX (7%), Black/African American (3%), American Indian or Alaska Native (1%), multiple races/ethnicities (12%), and Other (1%). Their ages ranged between 18 and 59 years old ( $M=31.2$  years,  $SD=7.1$  years). Most participants were employed (84%) and married

or in a committed relationship (67%). About a third (36%) reported having dependent children. From the participants' demographic information, it is evident that the online learners tend to be diverse (Safford & Stinton, 2016).

## Procedure

Invited students were eligible to participate if they were enrolled in at least one online course during the study. Each participant was surveyed twice weekly during their 7.5-week course using their preferred mode of communication (email and/or SMS message), as indicated in an initial screening survey. Participants were given a 48-hour window time to respond to each survey and a reminder to take each survey within 24 hours of survey administration. Participants received a \$5 Amazon gift card for completing at least one of two weekly surveys they received and \$15 for completing both. We used the survey data specific to week 4 (i.e., the midpoint of the course duration) as the data for the current study.

## Survey Instrument

The survey instrument measures students' individual characteristics, course perceptions, and course-level persistence intentions (refer to Figure 1). The individual characteristic variables on the survey include expectancies of course success and subjective course task values (i.e., students' intrinsic, attainment, and utility-related motivations for taking the course). The course perception measures on the survey include perceptions of instructor practices, perceptions of peer support, perceptions of course LMS (LMS dialog and LMS fit), and perceptions of course difficulty. All scales were measured on a five-point Likert scale ranging from 1=strongly disagree to 5=strongly agree. Table 1 shows the number of items, example items, and Cronbach's alpha values for each scale used in the study. The score for each scale was calculated by averaging the set of items scores associated with the scale. No missing data was found in the survey responses related to the scales. For more information about this survey instrument, its associated scales, and items in each scale, the readers are directed to Lee et al. (2020).

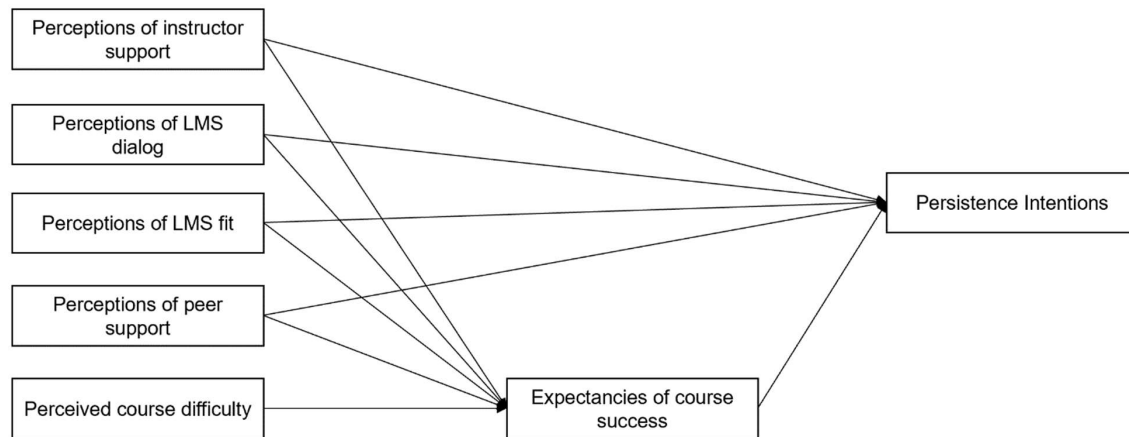
Table 1. Overview of the scales of the instrument (Lee et al., 2020)

Scale (# of Items)	Definition	Example Items	Cronbach's $\alpha$
Perception of instructor support (8)	Students' perceptions of the instructor's classroom practice and behavior in the online course environment	<ul style="list-style-type: none"> <li>The instructor incorporates a variety of different approaches to learning.</li> <li>The instructor explains concepts in a way that makes them easy to understand.</li> </ul>	0.95
Perception of peer support (6)	Students' perceptions of peer connectedness and support in the online course environment	<ul style="list-style-type: none"> <li>I have access to peer support in this course.</li> <li>I can join study groups with other students in the course if I want to.</li> </ul>	0.90
Perception of course LMS fit (4)	Students' perceptions about the fit between course and online learning platform	<ul style="list-style-type: none"> <li>I am satisfied with the format of the material provided.</li> <li>I am satisfied with the technology used in this course.</li> </ul>	0.87
Perception of course LMS dialog (4)	Students' perceptions about the opportunity for dialog with others in the online learning platform	<ul style="list-style-type: none"> <li>I feel comfortable using the course Canvas site to converse with others.</li> <li>I feel comfortable using the course Canvas site to ask questions to others.</li> </ul>	0.92

Perceived course difficulty (5)	Students' perceived level of difficulty to complete the required tasks in their online course	<ul style="list-style-type: none"> <li>• I find the tasks required in this course to be hard.</li> <li>• I find that this course is difficult.</li> </ul>	0.94
Expectancies of course success (5)	The extent to which students feel confident in their ability to complete their online course	<ul style="list-style-type: none"> <li>• I can meet the goals set out for me in this course.</li> <li>• I can satisfy the objectives for this course.</li> </ul>	0.93
Course-level persistence Intentions (5)	The extent to which students intend to complete their online course	<ul style="list-style-type: none"> <li>• I intend to complete this course.</li> <li>• I am fully committed to completing this course</li> </ul>	0.88

## Path Analysis

Path analysis was used to identify the individual and course characteristics that most influence students' persistence decisions in online undergraduate engineering courses. We also tested whether students' course perceptions influenced their persistence intentions directly or indirectly, through expectancies of course success. The path diagram for the model under study is described in Figure 2. In the model, we examine both the direct and indirect effects of perceptions of instructor support, perceptions of LMS dialog, perceptions of LMS fit, perceptions of peer support, and perceptions of course difficulty on students' course-level persistence intentions. To assess how well a model fits the data a chi-square ( $\chi^2$ ) estimate is used, a relatively low chi-square value (closer to zero) indicates a better model fit (Kline, 2005). The other indices used to assess the model fitness include comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root means square residual (SRMR). The values of these indices that indicate the level of acceptableness are CFI  $\geq$  0.90 (good) and CFI  $\geq$  0.95 (excellent), RMSEA  $\leq$  0.10 (good) and RMSEA  $\leq$  0.05 (excellent), and SRMR  $\leq$  0.08 (Sun, 2005). Table 2 presents the means, standard deviations, and correlations among all the variables considered in this study.



**Figure 2: Block diagram of the hypothesized model**

Table 2. Means, standard deviations, and correlations among variables.

Variable	1	2	3	4	5	6	Mean	SD
1. Instructor support	-						3.4	1.0
2. LMS dialog	0.31**	-					3.5	1.1
3. LMS fit	0.66**	0.53**	-				3.7	0.9
4. Peer support	0.47**	0.41**	0.44*	-			3.5	0.9
5. Course difficulty	-0.26**	-0.12	-0.23**	-0.19*	-		3.5	1.1
6. Course success	0.51**	0.35**	0.55**	0.44**	-0.40**	-	4.1	0.8
7. Persistence Intentions	0.43**	0.31**	0.42**	0.38**	-0.27**	0.62**	4.6	0.6

Note.  $N=138$ , \* $p<0.05$ , \*\* $p<0.01$

## Results

The model tested in this study fit the data well across the model fitness indices, all of which were within their levels of acceptableness as described previously ( $\chi^2(1)=0.107$ ,  $p=0.744$ ,  $RMSEA<0.05$ ,  $CFI=1.00$ ,  $SRMR=0.004$ ). The final model with standardized estimates and standard errors in parentheses is shown in Figure 3 – bold highlighted numbers on the arrows indicate where effects were statistically significant ( $p<0.05$ ). Findings from the path analysis revealed that students' perceptions of LMS fit ( $p=0.003$ ) and perceived course difficulty ( $p=0.007$ ) significantly predicted expectancies of course success (positively and negatively, respectively). Expectancies of course success ( $p=0.000$ ) positively and significantly predicted students' course-level persistence intentions. Therefore, Expectancies of course success was the most important influences as it had a direct effect on persistence intentions. The indirect effects from the path perceptions of LMS fit to expectancies of course success, and perceived course difficulty to expectancies of course success on course-level persistence intentions were statistically significant ( $\beta=0.148$ ,  $p=0.014$  and  $\beta=-0.13$ ,  $p=0.008$ ).

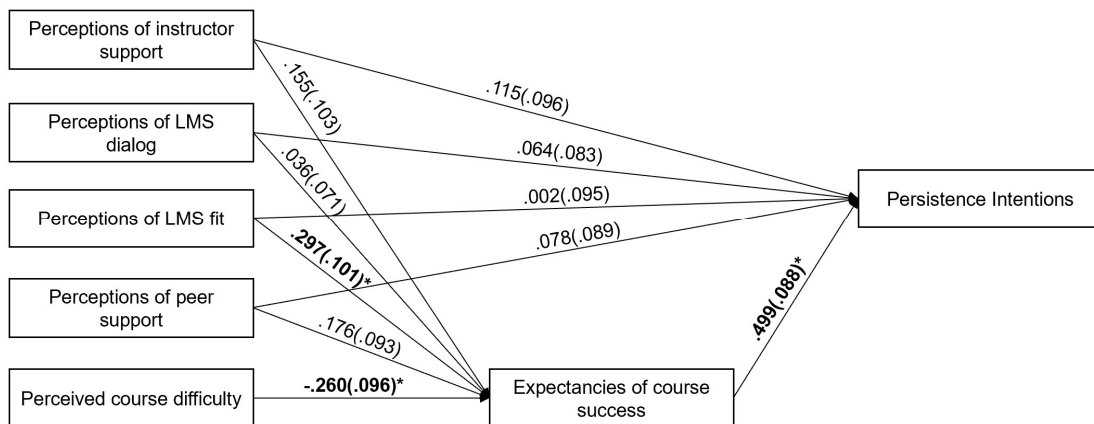


Figure 3: Model with standardized estimates and standard errors

## Discussions and Implications

The findings from this study reveal that perceptions of LMS fit (a course characteristic) and perceived course difficulty (an individual characteristic) had statistically significant predictive relationships with expectancies of course success (an individual characteristic) which in turn influenced students' persistence decisions in online undergraduate engineering courses. Previous studies have shown that perceptions of LMS influences students' persistence decisions in online courses. For example, Kittur et al. (2021) found perceptions of LMS to be a significant predictor of students' course-level persistence decisions while investigating the importance of interpersonal interactions in online undergraduate engineering courses. St Rose and Moore (2019) reported that accessing resources through the course LMS among other factors impacted student's retention in online courses. Course difficulty can be associated with student's persistence decision. Designing online courses with a focus on traditional students in mind can make the courses difficult for non-traditional students (a large part of students enrolled in online courses are non-traditional) (Robertson, 2020).

Expectancies of course success might be influenced by student's prior experiences related to online courses. Lee and Choi (2011) found that in addition to having greater internal locus of control, self-motivation, and course satisfaction, students with higher levels of confidence in their computer skills reported lower likelihoods of dropping out from their online course. Salvo et al. (2019) also found prior academic achievement, continuous academic enrollment, and previous information technology training to be some of the factors responsible for students' successful completion of online courses.

Institutions facing higher student dropouts in online undergraduate engineering courses must consider students' perceptions of LMS and perceived course difficulty as important aspects in online courses. Being aware of the students' beliefs related to the online courses can help faculty identify students at-risk of dropping out from the course. In addition, understanding students' expectancies of course success can help alert faculty members teaching online courses to students with reduced expectancies of being successful so that they can help these students persist. The students' perceptions on course LMS and their expectancies of course success can be measured by collecting data using the survey instrument presented in Lee et al., (2020), and the same can be monitored by collecting the data at different time points during the course to examine the changes in students' perceptions (if any).

## Conclusions, Limitations, and Future Work

In this study, a path analysis was conducted to investigate the role of course and individual characteristics on students' course-level persistence intentions within online undergraduate engineering courses. The findings from this study emphasize the importance of understanding students' perceptions of LMS and perceived course difficulty in online undergraduate engineering courses and the need to delineate further the mechanisms through which expectancies of success influence persistence.

This study comes with some limitations like any other study. The sample considered in this study was not representative of the entire online undergraduate engineering education community as the participants recruited in this study belonged to only one institution. Moreover, the data collected for this study is not sufficient to provide reasons to the findings, specifically answers like how and why perceptions of LMS, and expectancies of course success influence students' persistence decisions.

Further investigation is needed to examine the mechanisms through which perceptions of LMS and expectancies of course success influences persistence intentions. Notably, a potential future research direction in this area could be to conduct a qualitative study interviewing students to understand their experiences taking online undergraduate engineering courses and making course-level persistence decisions in their own words.

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## References

- ABET, Inc., "Online programs accredited by ABET," <https://amspub.abet.org/aps/online-search>, 2021 (Accessed June 2021).
- 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*.
- Bunn, J. (2004). Student persistence in a LIS distance education program. *Australian Academic & Research Libraries*, 35(3), 253-269.
- Frydenberg, J. (2007). Persistence in university continuing education online classes. *The international review of research in open and distributed Learning*, 8(3).
- 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).
- Heyman, E. (2010). *Overcoming student retention issues in higher education online programs: A Delphi study*. University of Phoenix.

- Kittur, J., Brunhaver, S., Bekki, J., & Lee, E. (2021, in press). Examining the Impact of Interpersonal Interactions on Course-Level Persistence Intentions Among Online Undergraduate Engineering Students. In Proceedings of American Society of Engineering Education.
- Kline, R. B. (2005). Principles and practice of structural equation modeling 2nd ed. *New York: Guilford*, 3.
- 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*.
- Lee, Y., & Choi, J. (2011). A review of online course dropout research: Implications for practice and future research. *Educational Technology Research and Development*, 59(5), 593-618.
- 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)
- 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.
- Moore, MJ 1993, 'Three types of interaction', in K Harry, M John & D Keegan (eds.), *Distance Education Theory*, Routledge, New York, pp. 19-24.
- 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., Dymont, J., Freeman, E., & Hopwood, B. (2019). Chronicling engagement: students' experience of online learning over time. *Distance Education*, 40(2), 262-277.
- 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.
- Robertson, S. G. (2020). Factors That Influence Students' Decision to Drop Out of an Online Business Course. (*Dissertation Thesis*).
- Rovai, A. P., & Downey, J. R. (2010). Why some distance education programs fail while others succeed in a global environment. *The Internet and Higher Education*, 13(3), 141-147.
- Safford, K., & Stinton, J. (2016). Barriers to blended digital distance vocational learning for non-traditional students. *British Journal of Educational Technology*, 47(1), 135-150.
- 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.
- Seaman, J. E., Allen, I. E., & Seaman, J. (2018). Grade Increase: Tracking Distance Education in the United States. *Babson Survey Research Group*.
- 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.
- 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.
- Sun, J. (2005). Assessing goodness of fit in confirmatory factor analysis. *Measurement and evaluation in counseling and development*, 37(4), 240-256.
- Wigfield, A., & Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemporary educational psychology*, 25(1), 68-81.
- Willging, P. A., & Johnson, S. D. (2009). Factors that influence students' decision to dropout of online courses. *Journal of Asynchronous Learning Networks*, 13(3), 115-127.
- 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.



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