How Online Learning Readiness Can Predict Online Learning Emotional States and Expected Academic Outcomes: Testing a Theoretically Based Mediation Model

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Abstract
During the pandemic, online courses became the major delivery format for most institutions of higher learning across the United States and around the world. However, many students experienced emotional distress as a result and have struggled to adapt to remote learning. To explore how emotional distress relates to other aspects of online learning, including online learning readiness and academic outcome, we asked a sample of 80 college students to participate in an online survey in the fall semester of 2020. Two distinct online learning readiness patterns were found using k-means cluster analysis. Online learning-ready learners showed statistically significant differences from the not-ready online learners on anxiety, boredom, and satisfaction. Moreover, a three-path mediation model based on a theoretical relationship between online learning readiness, emotional state, and expectation of learning outcome was tested using structural equation modeling (SEM). Results showed that readiness positively predicted satisfaction; furthermore, only satisfaction predicted learning expectation and expected grade. The implications of these findings and limitations of the study are discussed.

Keywords: online learning readiness, emotional states, mediation model, online learning outcome

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Due to the COVID-19 pandemic that started to spread widely in the United States in March of 2020, approximately 300 U.S. universities transitioned from face-to-face to online learning (Foresman, 2020), with online courses soon becoming the major delivery format for most institutions of higher education across the country. However, not all students succeeded in online learning environments; many experienced emotional distress and struggled to adapt. Assuming online instruction will continue to play a major role in higher education, identifying whether students are prepared for online learning is a necessary first step to ensuring success for online learners.

A state of preparedness for learning (also known as readiness) is essential for performance excellence. This applies not only in an online learning environment (Hung et al., 2010), but improves the learning experience and outcomes regardless of course delivery format (i.e., online, or offline) (Hung et al., 2010; Watson, 1996). Preparations for learning include, but are not limited to, students reviewing or reading materials ahead of time and maintaining a positive attitude and motivation toward learning. Teachers can help students get ready for learning through in-class activities, dividing assigned materials into smaller blocks, and modifying the classroom-related environment (e.g., rearranging the furniture such as using long table or round table for more discussions in traditional educational setups).

However, in an online learning environment, learners inevitably bear most of these responsibilities on their own, such as proactively creating a proper environment for online course since there is no physical classroom and the students may change their study environment from campus to home. Therefore, online learning readiness consists not only of the more traditional aspects of learning readiness but also additional aspects such as the learning environment. Even though the relations between online learning readiness and related learning aspects such as emotional status and academic outcome have been examined previously, no study to date has looked at all these different aspects simultaneously (Hung et al., 2010; Martin et al., 2020; Wang et al., 2022; Zhu et al., 2022). To fill this gap, in the current study, we first examined potential underlying subgroups of learners based on their profile of online learning readiness, followed by a mediation model addressing how online readiness predicted the expected grade through both emotional states and academic expectation. The goal of the study was to gain a more complete picture of the online learning mechanism from the perspective of online learning readiness.

Review of the Related Literature

Online Learning Readiness

Several online learning readiness scales have been used in previous research. For example, Hung and her colleagues (2010) included five dimensions of learning preparedness in their Online Learning Readiness Scale (OLRS): self-directed learning, motivation for learning, computer/internet self-efficacy, learner control, and online communication self-efficacy. Briefly, *self-directed learning* measures learners' control of their learning process. For example, self-directed learners can carry out their study plan independently. *Motivation for learning* measures whether students are motivated to learn. *Computer/internet self-efficacy*, in turn, addresses self-efficacy in terms of accessing online learning platforms and managing IT equipment. *Learner control* assesses the level of control with which students decide what, when, where, and how to learn. Finally, *online communication self-efficacy* refers to a special type of ability to communicate with instructors or classmates that is required in online settings since teachers and classmates are rarely reachable in person in a virtual classroom setting. Through these subscales, the OLRS allows learners to evaluate their state of readiness for online courses. In particular, the last three subscales are directly related to online learning scenarios. Nonetheless, this scale does not address how attentions or course materials may relate to readiness.

Martin et al. (2020) summarized the existing online student readiness survey instruments (e.g., Bernard et al., 2004; Kerr et al., 2006; Mattice & Dixon, 1999; Zimmerman & Kulikowich, 2016) and created their own self-assessment instrument. Specifically, based on a Google search, they identified four domains (online student attributes, time management, communication, and technical) that are related to the competencies of student readiness for online learning.

In another effort to develop an online learning readiness tool, Yu and Richardson (2015) created 20 self-reported items to make up their Student Online Learning Readiness (SOLR) instrument focusing on four components—social competencies with the instructor, communication competencies, social competencies with classmates, and technical competencies. In a subsequent study, Yu (2018) examined the construct validity of the SOLR, confirming that the instrument can be useful for measuring students' level of readiness for online learning before they take an online course. In addition, Liu (2019) evaluated the effects of an online learning orientation course on SOLR with a single-group pre- and post-test design. The results supported the use of SOLR for evaluation and planning for online student support.

As illustrated, most of the existing online readiness instruments focus only on specific learner competencies (e.g., technical competencies and social competencies) (Hung et al., 2010; Yu & Richardson, 2015). Yet, the requirements for being ready to learn in an online environment include a wide variety of factors such as the format (e.g., synchronized vs. asynchronized delivery format) and the content of online courses (Zheng et al., 2020). Moreover, until recently (Chien et al., 2020), there was no online learning readiness instrument created by using machine learning techniques. Chien and colleagues (2020) adopted a machine learning approach to first exclude the online readiness items that are not directly related to learning outcome and for those retained items which could be further categorized as students' behaviors and attitudes related into four dimensions through factor analysis. These four dimensions (and the corresponding subscales)—perceived attention problems under the online learning environment, environmental structuring, independent learning, and perceived unattractive course materials—make up the foundation of their Online-learning REadiness Scale (ORES; Chien et al., 2020). The details of these dimensions are discussed below, and the corresponding constructs are presented in the hypothesized model shown in Figure 1.

Due to the many potential distractions (e.g., social media notification) in the online learning environment, the ability to identify issues related to inattention is an essential part of preparing for successful online learning. Additionally, online learners need to prepare their own learning environment since there is no physical classroom; indeed, creating a supportive learning environment has been found to improve distance education and online learning performance (Ng, 2021). To that end, the ORES subscale of environmental structuring measures how well the learning environment is prepared. Given that online students need to play an active role in their own learning (e.g., proactively arrange their study schedule and hours rather following whatever the school determines), they must be self-regulated and independent to succeed (Carter et al., 2020). Hence, items that measure self-regulation and independence are important parts of the readiness construct. The fourth subscale perceived boring/uninteresting course materials, measures students' perspective on the course materials whether they are provided in a dull way. Although determining the attractiveness of course materials can be subjective and vary widely across learners, online learners generally agree that unattractive course materials make them "feel bored." (Ding & Zhao, 2020) In other words, students' emotional status is likely related both to the course content and their overall readiness to online learning.

Given the newly developed ORES (Chien et al., 2020), it is of interest to examine any possible underlying subgroups of learners displaying different patterns of online learning readiness. Such an exploratory analysis will provide a better idea of the readiness profiles of online learners, especially those who are struggling with the online learning environment, so that more effective interventions can be developed to help this group of learners succeed.

Emotional Status During Online Learning

Students' psychological perspective on their readiness is an important factor and is directly related to their performance in the online learning environment. Moreover, students' emotional status must be taken into consideration because it is not only linked with their cognitive ability but also their learning performance, which can be fostered or hindered by emotional experiences (Dirkx, 2008; Lehman, 2006; Pekrun et al., 2011).

In traditional learning environments, several studies have found that positive emotions such as enjoyment positively predicted student effort and academic performance, whereas negative emotions such as anxiety and boredom negatively predicted academic attainment and, overall, were more associated with lower levels of performance (Pekrun et al., 2009, 2011). When transitioning from a traditional face-to-face to an online learning environment, negative emotions such as anxiety and distress can be triggered due to the unfamiliar learning environment or limited social exchange. St. Clair (2015) stressed the anxiety problems of online learners, especially first-time online students. Similarly, Butz et al. (2015) found that online learners exhibited significantly higher levels of technology-related fear, anger, and helplessness than students in traditional classes. Furthermore, according to Hara and Kling (2000) and Abdous (2019), frustration, isolation, anxiety, and confusion are the most frequent feelings experienced by learners in online learning environments. Finally, compared with face-to-face courses, students might feel less satisfied with online courses (Tratnik et al., 2019).

Academic Expectations and Their Relation to Emotional Status in Online Learning

Expectation can directly motivate behaviors (Wigfield & Eccles, 2000). At the same time, different forms (i.e., positive and negative) of emotional status can predict the level of expectation. Indeed, the three emotional variables—anxiety, boredom, and satisfaction—studied here are related to students' academic expectation. Anxiety and boredom often result from inaccurate expectation of course difficulty (Csikszentmihalyi, 1990). That is, learners are likely to feel anxiety when the course difficulty is higher than they expect. On the contrary, learners can reach a state of boredom if the course content is easier than expected. Course satisfaction usually relates to the learner's expectation of the course quality as well as the actual learning experience. Thus, academic expectation was hypothesized to serve as a mediator in the relation between emotional status and expected grade.

In sum, academic emotions play a critical role in the overall learning processes; yet the relationship between students' online learning readiness and their emotional experiences in the online learning environment has not been thoroughly examined. In addition, knowledge about how students' emotional status is related to their expected academic achievement in the online learningenvironment remains limited. Therefore, the purpose of this study was to investigate the role of college students' online learning readiness in the online learning process and how it predicted their emotional states (e.g., anxiety, boredom, and satisfaction) and academic expectations, which, in turn, predicted their final expected grade. The hypothesized model as presented in Figure 1 is a full mediation model with online learning readiness as the exogenous variable, along with different emotional states and academic expectation as the mediators. Expected grade served as the target outcome variable.

The specific research questions were as follows:

H1: How many potential subgroups of online learners could be found based on the online learning readiness profile?
H2: Does online learning readiness predict the three emotional states (i.e., anxiety, boredom, and satisfaction)?
H3: Do the three emotional states (i.e., anxiety, boredom, and satisfaction) further predict students' academic expectation?
H4: Do the three emotional states (i.e., anxiety, boredom, and satisfaction) fully mediate the relation between online learning readiness and academic expectation?

Method

Participants and Procedure

Data were collected during the fall semester of 2020 on students recruited from a large public university in Texas. A recruitment email with the online survey link created by Qualtrics was sent to students by several academic advisors and instructors who were teaching large sections of undergraduate and graduate-level courses. Students who had enrolled in at least one synchronous or asynchronous onlinecourse were invited to participate. Students who consented to participate and completed the survey were rewarded with a $10 gift card. We estimated that the recruitment email reached roughly 1,000 students, of whom 106 clicked the survey link. The final sample consisted of 80 students, who completed the survey (63 females, 17 males). Of these 80 students, 58 were undergraduate and 22 were graduate students.

Measures

Online-Learning Readiness Scale (ORES)

We adopted a multifaceted 14-item ORES developed by Chien and colleagues (2020) to measure online learners' psychological readiness. A confirmatory factor analysis (CFA) entrenched four subscales: perceived attention problems under the online learning environment, environmental structuring, independent learning, and perceived unattractive course materials. *Perceived attention problems under the online learning environment* addressed readiness of focus on the course. For example, "When I see or hear notifications from social media (e.g., Twitter, Instagram, Facebook), I cannot wait to check them." Answers were given along a 5-point scale from 1 (not at all like me) to 5 (very much like me). *Environmental structuring* addressed the setting of the learning environment, including questions like "I choose the location where I study for this online course to avoid too much distraction." Answers were given along a 7-point scale from 1 (not at all true for me) to 7 (very true for me). *Independent learning* assessed whether the learner was ready to learn independently, ranging from 1 (strongly disagree) to 5 (strongly agree) (example question: "I am capable of solving problems alone"). Finally, *perceived unattractive course materials* addressed the learner's perspective of the course materials, for instance, "The design of this online class looks dry and unappealing." Answers were given along a 5-point scale ranging from 5 (very true) to 1 (not true). ω total was used to check the reliability of the instrument (McDonald, 1999). In this four-factor measurement, ω total for the total score was 0.78; the ω total for each subscale was 0.65, 0.64, 0.52, and 0.79, respectively.

Online Learning Anxiety

We also developed an eight-item online learning anxiety scale to assess the degree to which students felt anxious towards the online learning environment. Anxiety surrounding unfamiliar learning gadgets in an online learning scenario was added to the original learning anxiety; therefore, the scale included the dimensions of "Anxiety Due to Lack of Guidelines and Technical Knowledge for the Online Course" and "Anxiety Due to Lack of Academic Confidence in Their Ability for the Online Course." An example question from the former subscale was "A lack of clear instructions and/or feedback from the instructor in this online course would challenge me." An example question from the latter subscale was "I feel an inability to manage this online course workload." Answers were given along a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). Reliability coefficients (Cronbach's α) for the two subscales were .72 and .86, respectively.

Shortened Boredom Proneness Scale (SBPS)

The shortened eight-item SBPS was adapted by Struk et al. (2017) from the original Boredom Proneness Scale (BPS) developed by Farmer and Sundberg (1986). The SBPS has demonstrated unidimensionality and was used to assess propensity to experience boredom. For example, "Many things I have to do are repetitive and monotonous." Answers were given along a 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). A high score on this scale reflects a high propensity to feeling bored. The reliability coefficient (Cronbach's α) of the scale was .83.

Online Course Satisfaction Scale (OCSS)

The seven items of the OCSS (Wei & Chou, 2020) were adopted to assess students' general level of contentment with the learning experience related both to instructors and course design. For instance, "I am satisfied with the instructional style." Besides the different aspects of satisfaction, a summary question, "Overall, I am satisfied with this course," was asked at the end of the scale. Answers were given along a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). The reliability coefficient (Cronbach's α) of the scale was .84.

Academic Expectations

The academic expectations scale (Chemers et al., 2001) was used to assess students' expression of their expectations for future academic performance in their online course, including performance in courses, getting good evaluations, meeting academic goals, and generally performing well academically. Answers were given on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). The scale's reliability coefficient (ω total) was .66.

Expected Grade

Students' expected grade (A or non-A) consisted of their expected academic outcome for the online course they were taking.

Data Analysis Procedures

K-Means Clustering

K-means clustering is a multivariate person-centered exploratory approach that separates individuals into underlying subgroups based on a profile of a set of variables (Hartigan & Wong, 1979). This study applied k-means clustering to discover possible learner types in the data. K-means is an unsupervised learning algorithm that divides people (i.e., students/online learners in our data) with similar characteristics into groups (or clusters) without any preexisting grouping labels. With a chosen number of clusters and profile variables, k-means algorithm minimizes the intra-cluster variance that would divide data into the most distinct groups by calculating within cluster sum of square iteratively.

The number of clusters and initial points is essential to k-means clustering and determines the final cluster solution. Several methods assisted the researchers in deciding on the number of clusters, such as the elbow method, silhouette analysis, Davies-Bouldin index, and cubic clustering criterion (Davies & Bouldin, 1979; Ketchen & Shook, 1996; Kodinariya & Makwana, 2013; Sarle, 1983). Given that the students' readiness was the major focus of the study, we used the four ORES subscales as the clustering profile variables. The final group profile helped us to understand the characteristic of each subgroup.

Independent Sample *t*-Tests with External Variables

After obtaining the subgroups from the k-means clustering analysis, we investigated the group difference using independent *t*-tests with a set of external variables (i.e., variables not included in the k-means clustering). Three emotional variables—anxiety, boredom, and satisfaction—served as the external variables. The independent *t*-tests were carried out to compare the mean score difference between the groups on these three emotional variables.

Testing the Hypothesized Model via Structural Equation Modeling (SEM)

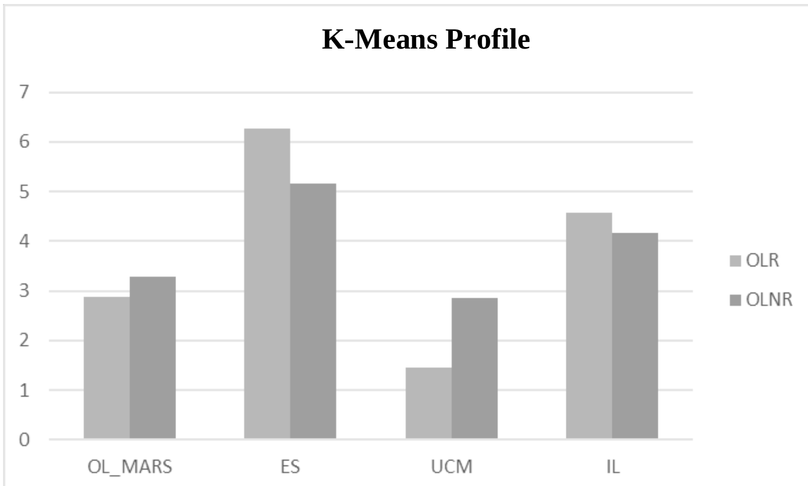
Structure equation modeling (SEM; Kline, 2016) was applied to estimate our hypothesized model, as shown in Figure 1. There are several advantages to using SEM. First, it estimates all the paths simultaneously (MacKinnon, & Luecken, 2008), unlike the multiple-regression approach (Baron & Kenny, 1986). Since SEM allows multiple endogenous variables in a model, a multiple-mediator model is possible. In the hypothesis model, three emotional variables—anxiety, boredom, and satisfaction—provided three possible mediation paths. Academic expectation served as a mediator between emotional status and the outcome variable, expected grade. SEM was the preferable estimation method due to the complicity of this model. Mplus (V8.6; Muthén & Muthén, 1998–2017) was used for the analysis.

Second, SEM provides model fit indices, another benefit of this type of analysis. Fit information offers evidence of whether the hypothesis model is approaching the data. Goodness of fit was evaluated by chi-squared test, RMSEA, CFI, and SRMR.

Results

To identify potential subgroups based on the four ORES subscales, we applied the k-means clustering procedure in RStudio (RStudio Team, 2015) with R-4.0.2 (R Core Team, 2020). Moreover, we compared multi-cluster solutions to find a suitable number of clusters using the cubic clustering criterion (CCC) under the NbClust Package (Charrad et al., 2014).

Figure 1
Cluster results of Online-Learning Readiness Scale (ORES)



Note. OL_MARS = perceived attention problems under the online learning environment; ES = environmental structuring; UCM = perceived unattractive course materials; IL = independent learning; OLR = Online-Learning Ready (OLR) Learners; OLNR = Online-Learning Non-Ready (OLNR) Learners.

As illustratedin Figure 1, this led to a two-cluster solution, with Cluster #1 (N = 44), named the Online-Learning Ready (OLR) Learners, reporting higher scores on both environmental structuring and independent learning and lower scores on both perceived unattractive course materials and attention problems under the online learning environment. By comparison, students in Cluster #2 (N = 36) scored in the opposite direction on the four ORES subscales; that is, they reported higher scores on both perceived unattractive course materials and attention problems under the online learning environment and lower scores on both environmental structuring and independent learning. Based on that profile, students in Cluster #2 were named the Online-Learning Not-Ready (OLNR) Learners. In addition, as shown in Table 1, significant mean differences on three emotional states (anxiety, boredom, and satisfaction) during online learning were found between the two groups: the OLR Learners had statistically significant lower anxiety (t = -2.53, p < .05) and boredom (t = -4.40, p < .001) scores and higher satisfaction scores (t = 4.94, p < .001) than the OLNR Learners.

A hypothesized three-path mediation model for how students' online learning readiness predicted their online learning emotions and performance was also tested using SEM. Specifically, we tested the potential mediation mechanisms of participants' emotional states during online learning (i.e., anxiety, boredom, and satisfaction) and academic expectations based on whether online readiness predicted the final expected grade in an online learning environment.

Table 1

Mean Values of the Emotional Factors During the Online Classes Across ORES Profile

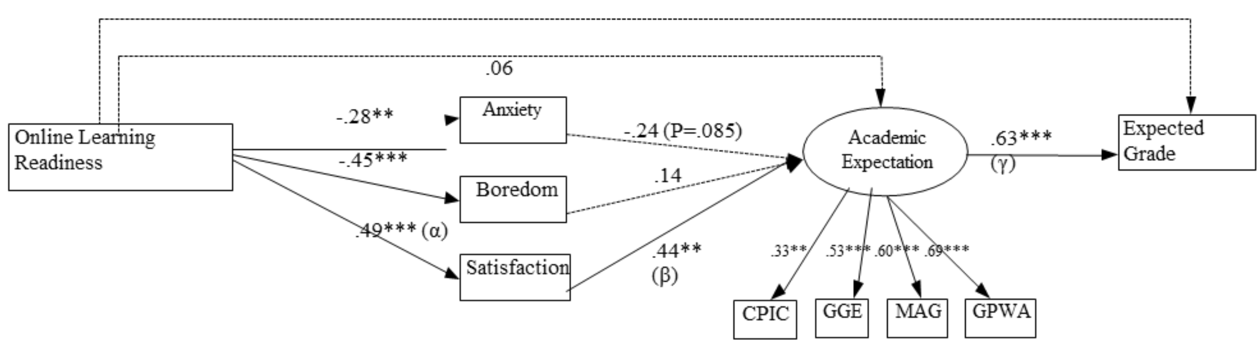
	C1: Online-Learning Ready (OLR) Learners (*N* = 44)		**C2: Online-Learning Non-Ready (OLNR) Learners (*N* = 36)**		***t*-test**
	M	***SD***	***M***	***SD***	
Anxiety	2.21	.88	2.73	.95	-2.53*
Boredom	2.52	1.09	3.58	1.05	-4.40***
Satisfaction	4.10	.65	3.39	.63	4.94***

*p < .05. ***p < .001.

As shown in Figure 2, the OLR Learners with higher online learning readiness scores had lower online anxiety (β = -.28, $p < .01$) and boredom (β = -.45, $p < .001$) but higher satisfaction scores (β = .49, $p < .001$) than the OLNR Learners. Furthermore, neither anxiety nor boredom significantly predicted academic expectations for all participants regardless of their readiness status (β = -.24, $p > .05$ and β = .14, $p > .05$, respectively). Only satisfaction significantly and positively predicted academic expectations (β = .44, $p < .01$), which, in turn, significantly and positively predicted the final expected grade (β = .63, $p < .001$). The overall mediated effect ($\hat{\alpha\beta\gamma}$) was examined using the bootstrap method (Cheung, 2007); the 95% confidence interval of the mediated effect fell between .07 and .64, which did not include zero, indicating that the overall mediated effect was significant. Therefore, both satisfaction and academic expectations were significant mediators.

Figure 2

Hypothesized Mediation Model



χ^2 (23, N = 80) = 31.689 (p = .107), RMSEA = .07, CFI = .91, and WRMR = .84

Note. All the coefficients are standardized. Dashed lines represent no significant association. CPIC = concerning performance in courses; GGE = getting good evaluations; MAG = meeting academic goals; GPWA = generally performing well academically.

**p < .01. ***p < .001.

Discussion

Prior researchers have explored partial relations among online learners' readiness, emotion state, academic expectation, and learning outcome (e.g., Hung et al., 2010; Martin et al., 2020; Wang et al., 2022; Zhu et al., 2022). The present study took a further step by putting together a theory-driven hypothesized model that incorporated several important aspects of online learning, including online learning readiness, different emotional states during online learning, learning expectations, and the expected learning outcome. Our goal was to gain a more complete picture of the online learning mechanism through the online learning readiness and related aspects. Two types of online readiness learners were found. Also, a fully mediated effect from readiness to learning outcome through the level of learning satisfaction and academic expectations was found.

Through cluster analysis, we identified two types of online learner profiles via the ORES: TheOnline-Learning Ready (OLR) Learners and the Online-Learning Not-Ready (OLNR) Learners. Group membership exhibited mean differences in anxiety, boredom, and satisfaction when participating in online courses. Specifically, the OLR Learners felt lower anxiety and boredom but higher satisfaction than the OLNR Learners.

These findings are similar to those of previous research. For example, when transitioning from a familiar face-to-face to an online learning environment that lacks a clear course roadmap of where to start or what to do, inexperienced or unprepared online learners tend to feel anxious or fear failure regarding their abilityto succeed in the unfamiliar learning environment (Ajmal & Ahmad, 2019; Zembylas, 2008). Further, Heckel and Ringeisen (2017) concluded that believing in their ability to handle the technology and content of online-learning platforms enhances the subjective relevance students attach to online learning, which, in turn, predicts lower boredom. Topal (2016) found that there was a positive significant relationship between students' levels of readiness and their satisfaction with e-courses.

In addition, SEM analysis in the present study found that OLR Learners with higher online learning readiness tended to feel less anxiety and boredom with their online courses and were more likely to report course satisfaction than the OLNR Learners. Moreover, anxiety and boredom did not significantly predict academic expectations; only satisfaction significantly and positively predicted academic expectations, which, in turn, led to higher grade expectations.

Consistent with previous studies, negative learning emotions are likely to impede students' learning (Tempelaar et al., 2012), whether in online or traditional courses. For example, for students entering college confident in their ability to perform well academically, their positive expectancy predicted better reactions during transitions to new academic environments (Chemers et al., 2001). Similarly, You and Kang (2014) found that while online learners' emotions of fear and boredom did not significantly influence self-regulated learning, feelings of enjoyment fostered self-regulated learning.

The major implication of our findings is that it is important to understand students' online readiness before they start taking online courses, especially for students who are new to the online learning environment. Thus, as needed, educators and policymakers can provide more support to improve students' positive emotion and satisfaction level such as offering compliments and incentives when students meet learning targets goals, which will likely lead to more positive expectations and higher expected performance.

A few limitations of the study warrant mention. First, self-reported expected grades instead of actual grades were used as the outcome measure. Clearly, while this is not ideal as the expected grade may be different from the actual grade, nevertheless, previous studies (Yeh et al., 2019) have found that the correlation between expected and actual grades was quite high. The second limitation involves the cross-sectional nature of the study. Our data provide a snapshot of students' emotional states (feelings of anxiety, boredom, and satisfaction). Future research should track individual students' emotional states over time. That is, a longitudinal study would provide a better understanding of the potential causal influences among the study variables over time, and an in-depth understanding of how students' readiness and feelings evolve can inform future online course design and support.

Further, the emotion state is a dynamic variable that changes throughout the course. Therefore, future studies should monitor the emotion state over time. A longitudinal study would provide more information about how emotion state can predict student's learning outcome. Another possible future study might categorize learners' latent group and profile to learn more about different types of readiness and how instructors can best instill them in students.

Lastly, the nature of the online course (e.g., a well-developed online course or an ad-hoc remote learning course due to COVID-19; synchronized or asynchronized) in which participants were enrolled was not obtained. Determining that might have some underlying confounding effect on study findings and, therefore, should also be examined in future studies.

Declarations

The authors declared no conflicts of interest.

All procedures performed in studies involving human participants were in accordance with the ethical standards and approval of Texas A&M University, USA.

Informed consent was obtained from all individual participants included in the study.

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