Understanding Course Success in Mandated Online Learning: The Role of Computer and Computer-Mediated Communication Anxiety

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Understanding Course Success in Mandated Online Learning: The Role of Computer and Computer-Mediated Communication Anxiety

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ABSTRACT

Amidst the COVID-19 pandemic, many universities shifted to fully online learning. This study contributes to the existing online learning literature by examining the connection between course success, student engagement, and levels of computer and computer-mediated communication anxiety. The research delves into understanding the impact of anxiety on course engagement and the relationship between engagement and overall course success. Regression analyses were used to test hypotheses, revealing an interaction between computer anxiety and computer-mediated communication anxiety. The study underscores the importance of student engagement with course materials, particularly for assignments that require higher-order thinking. In contrast, objective quizzes and tests that do not require higher-order thinking were unaffected by engagement. The findings emphasize the collective responsibility of professors, advisors, and universities to improve student engagement. Recommendations include structuring courses to address anxiety, employing gamification techniques for technical classes, and fostering connections through discussion boards in online courses. Increasing engagement emerges as a pivotal strategy for academic success.

Keywords: Computer anxiety, Communication anxiety, Distance education and online learning, Post-secondary education, Teaching/learning strategies

INTRODUCTION

Online instruction has been a part of higher education for over a decade. The degree to which an institution offers online courses varies from school to school, or at least it varied until the COVID-19 pandemic happened. In the spring of 2020, the vast majority of institutions were forced to deliver courses online in response to the pandemic. To this point, if an institution offered online courses, participation in the online course was optional as most universities also offered the same course in a face-to-face format (F2F). Never before had online learning been mandated. With social distancing guidelines from the CDC, large classes still had to be held online as universities began returning to F2F instruction
because classrooms large enough to hold 50, 75, or even 100 students and allow for 6 feet of space between each student were not available.

Learning online can be a challenge, particularly if the students were expecting and prefer a traditional F2F mode of course delivery (Riggs, 2019). Traditional F2F instruction exhibits several advantages over online instruction (Xu & Jaggars, 2014). First, it is more dynamic than online instruction, offering the opportunity for direct interaction between students and instructors, fostering immediate feedback, clarification of concepts, and personalized support (Sujatha & Bhuvaneshwari, 2021). Second, it is a well-established mode that students are used to using. Third, it does not rely on networked systems. Most importantly, students who preferred face-to-face classes demonstrated higher achievement test scores compared to those who preferred online classes, suggesting a potential correlation between preference for instructional modality and academic performance (Sekine et al., 2022; Xu & Jaggars, 2014). This indicates that students' comfort levels and performance outcomes may be influenced by their mode of instruction. To address the challenges of online learning, understanding the root cause of this performance difference becomes important.

Looking at Massively Open Online Courses (MOOCs), the percentage of students that complete those types of courses is exceedingly low. The two leading indicators of course completion in a MOOC are course content and interactions with the course instructor (Hone & El Said, 2016). Course content and instructor interaction are important building blocks of student engagement. In a mandated online setting where the environment is less dynamic and limited to the speed of the students’ connection to the internet, student engagement becomes even more important to student success.

Despite popular media portrayals of Millennials and Gen Z as tech-savvy, only 2 percent of students reach the highest level of computer and information literacy and computational thinking skills implied by the term “digital native” (National Center for Education Statistics, 2018). Furthermore, only 19% of respondents can work independently with computers as information-gathering tools. These numbers indicate that most students are not particularly tech-savvy, making their engagement with course content even more crucial.

When students are faced with a new and uncertain situation not of their own choosing, anxiety is often a result. Against the backdrop of a global pandemic, students either chose to delay their graduation and wait for F2F classes to resume, incurring the costs that come with delayed graduation, or they could shift to taking classes they otherwise would have taken F2F in an online environment. In fact, student anxiety has undergone significant changes since the onset of the COVID-19 pandemic. A recent meta-analysis found that the prevalence of anxiety symptoms during the pandemic was higher compared to pre-pandemic levels (Zhang, Bao, Yan, Miao, & Guo, 2021). Similarly, research on college students globally reported a higher prevalence of depression, anxiety, and stress during the pandemic (Daniali, Martinussen, & Flaten, 2023). Studies specific to medical students indicated that a large proportion experienced increased stress and anxiety levels due to the pandemic (Ewid et al., 2023; Lee et al., 2021).

Transitioning to an asynchronous online format sacrifices real time interactions between professors and students. Even in a synchronous online class, technical difficulties such as microphones being automatically muted so messages never get shared, or the inability for the professor to read the chat feed if their screen is being shared leading to students thinking the professor is ignoring them, or even slow internet speeds for some attendees all can make for a less interactive and less dynamic than the traditional F2F environment (Kemp & Grieve, 2014; Meade & Parthasarathy, 2024). An asynchronous online course would not have these issues because interactions between student and professor would typically happen on a case-by-case basis during virtual office hours and could be addressed prior to getting into the reason for the interaction. After all, who isn’t familiar with the online greeting of, “Can you hear me? Is my mic working?”

This research argues that course success hinges on student engagement and that the anxiety a student feels impacts their level of engagement. It seeks to provide answers to these two questions. First, what is the role of anxiety in students engaging with the course? Second, what is the role of engagement with course success? The next section develops a theoretical model and testable hypotheses to answer these questions.
THEORETICAL DEVELOPMENT

The Pandemic was an unprecedented event that not only impacted people’s lives but many industries as well. In answering the first research question, it is important to differentiate between state and trait anxiety. Over a half century ago, Spielberger (1966) developed the first model of state-trait anxiety. According to this model, state anxiety is temporarily brought on by being in a certain situation and is alleviated when the originating stimulus is removed. Trait anxiety is conceptualized as an individual’s tendency to respond to their environment with increases in state anxiety. This study does not address trait anxiety, only state anxiety is under investigation. Specifically, computer-mediated communication anxiety (CMCA) and computer anxiety are of interest because of their relevance to mandated online learning during the COVID-19 pandemic.

CMCA is defined as the fear or apprehension an individual experiences when using computers to communicate with others (S. A. Brown, Fuller, & Vician, 2004). Computer anxiety is defined as the tendency an individual has to be uneasy, nervous, fearful, or apprehensive about using a computer (Igbaria & Parasuraman, 1989). Computer anxiety might seem like a relic of the past due to the current ubiquity of computers and computing technology. When the internet was still considered new, about 40% of students surveyed reported feeling anxious about computers (Rosen & Weil, 1995). Over a decade later, a longitudinal study on computer anxiety found that close to 40% of students displayed computer anxiety (Buche, Davis, & Vician, 2007). Still more recently, studies found that computer anxiety negatively impacted course learning, course enjoyment, and perceptions of how easy a computer is to use (Faulconer & Griffith, 2022; Garris & Fleck, 2022; Kustono, 2022). During the pandemic, when universities only offered online courses, many students enrolled in online courses because there wasn’t any other option. Not only were many students apprehensive about exclusively using a computer to complete their coursework, but many of these students also enrolled in classes that exposed them to and expected them to become proficient with new pieces of software, thereby triggering computer anxiety. Compounding the matter was the fact that many universities shut down faculty offices and any student-professor interactions had to be conducted via the computer, thereby triggering a student’s potential CMCA. To have a successful interaction with their professor, a student must potentially overcome two different state anxieties. First, they must overcome any anxiety about using the computer to accomplish course tasks and second they must overcome any anxiety about using the computer as a communication tool.

Attentional Control Theory (ACT) forms the basis for the claim that anxiety impedes online student engagement (Eysenck, Derakshan, Santos, & Calvo, 2007). ACT was developed from Processing Efficiency Theory (Eysenck & Calvo, 1992) which claims that anxiety impedes attentional control by increasing one’s attention on threat stimuli i.e., an individual focuses on external task-irrelevant distractors or on internal worries about task performance. Online student engagement (OSE) refers to the quality of the effort students make to perform well and achieve desired outcomes in a course (Dixson, 2015; S. Hu & Kuh, 2002). The basic argument of the theory is that high levels of anxiety from either using a computer (i.e., computer anxiety) or as a communication tool (i.e., CMCA) prevent students from engaging with course material, and in turn these less engaged students do not perform as well in the course.

Hypothesis Development

The first research question investigates the role of anxiety on student engagement. Previous studies have demonstrated various factors that lead to the development of OSE. Factors such as instructor presence (Dixson, 2010), or motivation (Raes et al., 2020). However, this study is focused on factors that impede engagement. Following from the previous section, two types of anxiety are particularly apparent in online courses. First is computer mediated communication anxiety. Communication anxiety has demonstrated a long history with reduced learning and lower overall course performance (McCroskey, 2009). There is no reason to think that communication anxiety in online courses will be any less prevalent. During the COVID-19 pandemic, the only way for students to interact with professors was via some sort of computer mediated medium like Zoom or Microsoft Teams as social distancing guidelines and university policies designed to minimize the spread of the virus closed faculty offices. However, if a student is fearful or nervous about interacting with others via a computer, the students is more likely to fall behind, miss assignments, and be less engaged with course content, which suggests the following hypothesis:

H1: There will be a negative relationship between CMCA and OSE.
The second form of anxiety expected to impede OSE is computer anxiety. Those students who were anxious about using computers for course work and would have taken a course in person to minimize their use of a computer to accomplish course work were suddenly forced into online courses (Lester, Yang, & James, 2005). Thatcher and Perrewe (2002) found that students who were anxious about using computers also reported that they felt unable to complete computer-based tasks. It stands to reason that the level of course engagement would depend on the level of anxiety a student has about using computers for any task. This suggests the following hypotheses:

**H2:** There will be a negative relationship between computer anxiety and OSE.

If a student is anxious about using a computer to complete course activities in a traditional face-to-face class, they can meet with the professor and work together to alleviate the anxiety. However, in an online class, this avenue for interaction is not an option, but instead the student would need to meet via a computer. If that same student also has anxiety over using the computer as a communication tool, then the student would have to overcome two types of anxiety to be successful. Keeley, Zayac, and Correia (2008) demonstrate that the relationship between statistics anxiety (i.e., anxiety students display over taking a statistics course) had a curvilinear relationship with test performance. Those students with some anxiety outperformed those with low levels of anxiety and high levels of anxiety. With two different types of anxiety under investigation, these could interact thereby suggesting the following hypothesis:

**H3:** Computer anxiety will moderate the relationship between CMCA and OSE; OSE varies based on a student’s level of computer anxiety and CMCA.

The second research question asks, “what is the role of engagement with course success?” Engagement is a key element for student learning and academic success (Dixson, 2010, 2015; Fredricks, Blumenfeld, & Paris, 2004). Previous studies have demonstrated that engagement leads to increased learning (Goldberg et al., 2021), social presence (Wise, Chang, Duffy, & Del Valle, 2004), and better remembering (Greene, Dillon, & Crynes, 2003). Student engagement has been positively associated with student learning, satisfaction, success, and retention (P. J.-H. Hu & Hui, 2012; Oncu & Cakir, 2011; Vayre & Vonthron, 2014), and negatively associated with a student’s intention to dropout (Kim, Liu, & Bonk, 2005). More recently, an artificial intelligence recommendation system was used to increase course engagement (Huang, Lu, & Yang, 2023). However, OSE has not been linked to achievement within a single course. It is usually tied to overall learning across a degree program, or to graduation, or intent to reenroll. It makes sense that engagement leads to overall academic success. However, to be successful in a degree program or to graduate, a student must be successful in their individual courses as well. This suggests the following hypothesis:

**H4:** There will be a positive relationship between OSE and final course performance.

**Control Variables**

While the focus of the research is on computer anxiety, CMCA, and the interaction of these two types of anxiety on student engagement, other factors could also be influencing a student’s level of engagement with course material as well. Several other factors were also included as control variables. The benefits of including these control variables are twofold. First, by including these variables, this research is situated in a wider nomological network. Second, any effects due to anxiety are over and above the effects of the control variables. The control variables included in the model are e-propinquity, self-control, and coping.

**Electronic Propinquity**

E-propinquity is at the heart of mediated communication and its concepts predate the Internet and other forms of electronic communication like email, real time chat, or video conferencing tools commonly used in today’s pandemic world such as Zoom or Teams (Korzenny, 1978; Walther & Bazarova, 2008). E-propinquity is the subjective perception of nearness or proximity to another individual. Unlike the similar media richness (Daft & Lengel, 1984) or social presence (Short, Williams, & Christie, 1976), e-propinquity argues that the same source can be perceived as psychologically proximate to another individual when other options are not available.
An example of e-propinquity would be a student enrolled in a data visualization class who needs help in completing a class project. The student feels the source with the greatest propinquity would be meeting in their professor’s office. However, due to the COVID pandemic, all professor offices are closed. The student then would like to try meeting via Zoom, but it is not in the professor’s stated office hours, and a meeting via Zoom is unlikely to occur until it is office hours. The student then turns to several tutorial videos posted in the course learning management system as she feels that would be the source with the greatest propinquity. Unlike media richness, which would argue that face to face is the richest form of communication and tutorial videos are the leanest form or social presence which would say the perception of closeness diminishes with the decrease in bandwidth going from meeting in person to meeting online to watching videos, e-propinquity would argue that the student could perceive the professor just as closely in the video scenario is in meeting in person (Walther & Bazarova, 2008; Wombacher, Harris, Buckner, Frisby, & Limperos, 2017). Addressing these perceptions of nearness needs to be addressed in the model in order to better understand the impacts of anxiety on course engagement.

Self-control

Self-control is the ability to exercise intentionality over one’s behavior (Hofmann, Friese, & Strack, 2009). To engage with the course means that the student is focused on course content and is not engaging in other non-course activities. In an asynchronous online class, students are expected to work at their own pace and meet course deadlines. Because online learning was mandated to minimize the spread of COVID, many students are taking online courses for the first time and their self-control to stay focused on and engage with course material in this new environment is being tested for the first time. A student’s ability to regulate their behavior should be included to get a better understanding of how anxiety impacts student engagement.

Coping

The COVID pandemic placed unforeseen stresses upon everyone. One of the challenges for students was mandated online courses. While some students my prefer online courses, many do not and to have the option for in person classes stripped away is a stressful event. Coping has been broadly defined as an individual’s attempts at stress management (Holahan & Moos, 1987). Where anxiety can be viewed as a maladaptive response to stress, coping skills are an adaptive response to stress and the level of coping skills students have should be controlled in the model. The complete research model is shown in Figure 1.

Figure 1. Proposed Research Model
METHODS

This section details the study participants, measurements, and procedures used to collect the data.

Participants

Invitations to participate were sent to 459 undergraduate students enrolled in an online introductory information systems course. Of those invited, 266 (58%) completed the survey and 236 (51%) chose to make their course performance data available. Participants were not compensated for their time and the mean time to complete the survey was 9 minutes and 58 seconds (\(\bar{x} = 9:58, \text{SD} = 5:48\)). Participants were mostly of traditional college age (\(\bar{x} = 22.31, \text{s.d.} = 5.35\)) though 55 respondents were over 24 years old. Racially, respondents were 2% Asian (N = 6), 2% Latinx (N = 4), 8% multiracial (N = 21), 20% African American (N = 54), 62% Caucasian (N = 165), and 6% elected to leave the question blank (N = 16). Along gender lines, 51% was female (N = 136), 43% was male (N = 114), and 6% elected to leave the question blank (N = 16). Given that the course used to survey respondents was housed in the college of business and is required of all business majors, it is unsurprising that 95% of the sample were business majors. The remaining 5% of respondents were non-business majors. Most of the sample had previously taken an online course prior to the COVID-19 pandemic (N = 202, 80%), though 20% of the respondents (N = 50) took their first online course because they had no option as the university cancelled all face-to-face classes.

Measures

Survey items were taken from the literature, and all items and their anchors are shown in the Appendix. Computer anxiety was measured using six Likert items from the short computer anxiety scale (Lester et al., 2005). CMCA was measured using 10 Likert items from the computer mediated communication apprehension scale (Scott & Timmerman, 2005). OSE was measured using the 10 Likert item online student engagement scale (Dixson, 2015). Coping was measured using five Likert items from Holahan and Moos (1987) coping scale. Self-control was measured using eight Likert items from Tangney, Baumeister, and Boone (2004) scale of self-control. E-propinquity was measured using seven semantic differential items (Walther & Bazarova, 2008). All scales demonstrated acceptable reliabilities using Cronbach’s (Nunnally, 1978) (see Table 1). Additionally, all scales demonstrated acceptable construct validity based on an exploratory factor analysis where all individual items loaded onto its own factor. A confirmatory factor analysis was also conducted on the two anxiety measures, and these results showed good fit for these constructs. Assured that the scales used are reliable and valid, each scale’s items were combined to form a single measure for that construct in the subsequent analyses.

Course performance was measured using scores on four types of assignments. The first type, projects, were scores coming from assignments that required students to demonstrate proficiency with various software applications. The second type, papers, were scores coming from writing assignments about computer security and project management. The third type, quizzes, were scores coming from open book quizzes covering text material. The fourth type, tests, were scores coming from timed, closed book, proctored exams. All assignments were completed as individual work. There were no group assignments or team assignments in the course.

RESULTS

A series of regressions were conducted to test the study hypotheses. First, the analyses considering the antecedents to OSE are presented. Second, analyses considering the relationship between OSE and course performance are presented. Lastly, some post hoc analyses suggested by the results of the first two analyses are presented.

Antecedents to OSE Results

This section details the analysis of the antecedents to OSE. The next section presents the analysis to determine whether OLS based regression or MLE based multilevel modeling is required to formally test the hypotheses. The section following that presents the results of the hypothesis tests.
Results for the ICC Analysis for OSE

One of the assumptions of regression is the observations are independent, and if this violation is violated, the risk of making a Type I error, dramatically increases (Garson, 2020). It is well known that in educational research, the independence assumption is often violated when students’ performance is investigated due to grouping factors such as the teacher the student has, the school the student attends, or even the semester when the course was taken. All students surveyed had the same professor teaching the class though data were collected across two semesters. This means that there could be a semester effect in the data that needs to be addressed.

Checking for a nesting (or grouping) effect is done by calculating the item characteristic curve (ICC) for the grouping variable. The ICC shows the amount of the variability in the dependent variable that is attributable to the grouping factor, i.e., the ICC is a measure of whether the independence assumption is violated or not. Since all subjects were enrolled in the same professor’s course, there should not be a grouping effect for professor. When a grouping effect for semester was tested, the ICC turned out to be 0.01 meaning 1 percent of the variability in course performance can be attributed to the semester when the course was taken. There are no hard and fast rules about how large an ICC must be before the dependence in the data must be addressed, but a common rule of thumb is if an ICC under 0.10, then the independence assumption is valid (Gordon, 2019). Because the ICC was 0.01, the more parsimonious OLS regression was used as opposed to MLE based multilevel modeling.

Results for the OSE Antecedents

To test hypotheses 1, 2, and 3, a series of multiple regressions were conducted. Because the hypothesis of interest is an interaction of CMCA and computer anxiety all the study variables were standardized. Standardizing the variables in the analysis removes the effects of multicollinearity due to the creation of interaction terms (Aiken & West, 1991). The most common way to check for multicollinearity is to check the variance inflation factor (VIF) of an independent variable. A VIF greater than 2.5 is an indication of multicollinearity (Johnston, Jones, & Manley, 2018). All the independent variables displayed a VIF of less than 1.5 when using standardized variables. This was not the case when using mean centered variables, hence standardized values were used to conduct the following regression analyses. Descriptive statistics of the mean centered variables, the scale reliabilities, and correlations among the study variables are shown in Table 1.

| Descriptives | Cronbach | Correlations |  |  |  |  |  |  |  |
|--------------|----------|--------------|---|---|---|---|---|---|
| Descriptives | SD       | α            | OSE| EP| coping| SC| CMCA |
| OSE          | -0.013   | 8.441        | 0.87 | -- |
| e-propinquity (EP) | 0.018 | 10.84 | 0.89 | 0.247 | -- |
| coping       | 0.009    | 3.699        | 0.75 | 0.199 | 0.161 | -- |
| self-control (SC) | 0    | 5.632 | 0.81 | 0.268 | 0.192 | 0.268 | -- |
| CMCA         | 0        | 7.976        | 0.79 | -0.156 | -0.18 | -0.241 | -0.343 | -- |
| computer anxiety | -0.087 | 7.424 | 0.85 | -0.181 | -0.095 | -0.041 | -0.104 | 0.155 |

The regression was conducted in three phases. The first includes only the control variables, the second adds the main effects for CMCA and computer anxiety to the model. The final step of the regression adds the interaction of CMCA and computer anxiety. The results of these analyses are shown in Table 2. Considering the model where only the control variables are considered, e-propinquity and self-control are significantly related to OSE. The other control variable, coping, was not related to OSE. However, since coping displayed a strong correlation with CMCA, coping remains in the model. The second model added the main effects for CMCA and computer anxiety and tests Hypotheses 1 and 2. The same pattern of significance was observed with the control variables as the previous model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Controls Only Model</th>
<th>Main Effects Model</th>
<th>Interaction Model</th>
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Table 2. Regression Results for Hypothesis 1
Hypothesis 1 argues for a negative relationship between CMCA and OSE. This hypothesis was not supported ($\beta=0.012$, $t=0.179$, $p = 0.42$). However, Hypothesis 2 was supported. Computer anxiety displayed a significant relationship with OSE ($\beta=-0.137$, $t=-2.27$, $p=0.01$). When testing an interaction, lower order effects must remain in the model so despite not demonstrating a relationship with OSE, CMCA will remain in the model for subsequent testing. The third model formally tests Hypothesis 3, which argues that computer anxiety will moderate the relationship between CMCA and OSE. This hypothesis was supported ($\beta=-0.126$, $t_{(238)}=-4.02$, $p=0.0001$) meaning the relationship between CMCA depends on the amount a computer anxiety an individual has. The nature of this interaction will be explored in the following section.

**Simple Slopes Analysis**

Because computer anxiety moderates the relationship between CMCA and OSE, the exact nature of how computer anxiety differentially impacts the relationship between CMCA and OSE needs to be further analyzed. To understand the exact nature of the interaction, a simple slopes analysis was conducted (Aiken & West, 1991).

![Figure 2. Plot of Predicted OSE Values for Computer Anxiety x CMCA Interaction](image-url)
Before the simple slopes are presented, looking at the entire response surface of the interaction can be enlightening. With the regression equation, the predicted values can be calculated and plotted, and the results of this are shown in Figure 2. The basic shape of the interaction is a saddle shape. The predicted levels of engagement are highest when an individual is low on one form of anxiety and high on the other (e.g., low CMCA and high computer anxiety, or high CMCA and low computer anxiety). This indicates that some level of one type of anxiety so long as it is the only type of anxiety can act as a motivator and get students to engage with course material. If a student exhibits both types of anxiety, this leads to less engagement. The same is true if a student exhibits no traces of either type of anxiety. In the former case, a student can be overwhelmed by anxiety and unable to address it and never engage with the material. In the latter case it could be that the student looks at the course merely as a box to be checked on the way to a larger goal.

Turning to the simple slopes, this analysis takes slices through the surface at low, medium, and high levels of the moderator variable. The simple slope presentation would be akin to standing in front of the CMCA axis in Figure 2 and taking slices along the computer anxiety axis.

The general rule for determining low, medium, and high levels of a moderator is to use one standard deviation below the mean to be the low values, the mean to be medium values, and one standard deviation above the mean to be high values (Aiken & West, 1991). Since the data is standardized with a mean of 0 and a standard deviation of 1, regression lines for a computer anxiety of -1, 0, and 1 will be the values selected to represent low, medium, and high levels of computer anxiety.

Figure 3 shows the results of the simple slopes analysis. Depending on the level of computer anxiety an individual has, the nature of the relationship between CMCA and OSE varies dramatically. When an individual has high levels of computer anxiety, the relationship between CMCA and OSE is negative. The opposite is seen when an individual has low levels of computer anxiety. A possible explanation for this finding could be that students who are not intimidated by technology (i.e., have low levels of computer anxiety) are able to overcome their anxiety about using a computer as a communication tool and engage in an online course. Whereas those that are intimidated by technology (i.e., have high levels of computer anxiety) find it even harder to engage in an online course due to their anxiety about using computers and their anxiety about using computers as a communication device. The implications of this finding will be covered in the discussion section.

Figure 3. Graphs of Simple Slopes: The Relationship Between CMCA and Online Engagement at Three Different Levels of Computer Anxiety
The Impact of OSE on Course Performance Results

This section details the analysis of OSE on course performance. The following section presents the analysis to determine whether OLS based regression or MLE based multilevel modeling is required to formally test the hypothesis. The section following that presents the results of the hypothesis test.

Results for the ICC analysis for Course Performance

Much like when testing Hypothesis 1, there is potential grouping or clustering in the data. Each subject provides four different data points for course performance, as well as potential semester effects. This means the independence assumption for linear regression is probably invalid. Professor effects are not expected since the same professor taught all the students.

The ICC for this analysis shows the percentage of the variability in course performance that is attributable to the student and semester. The ICC for this analysis was 0.20, which is clearly large enough to show that the independence assumption is violated and should be addressed in subsequent analyses.

Hypothesis 2 Results

Because the ICC was 0.20, analyses that address the nonindependence in the data must be used which means a multi-level model was developed to test the hypothesis. The method to test the hypothesis was a four-step process. The first step was to fit a null model with no predictors. This allows for the calculation of the ICC and provides a baseline to compare with the hypothesized model. The second step was to add the predictors to the model. The third step was to compare the null model to the hypothesized model. The final step was to conduct any tests suggested by the findings in the third step.

Once the baseline model was run, the independent variables were added to the model and the model was run again. As compared to the baseline model, adding OSE, assignment type, and the interaction term of OSE and assignment type resulted in a superior model. There is no one test to assess the best fitting model. Instead, multiple statistics have been developed to assess model fit, each differing slightly in how they are calculated (Garson, 2020; Hox, 2010). The AIC, BIC, and -2LL are all common indicators of model fit, where lower scores are considered better. Additionally, the difference between -2LL scores is distributed as chi-square and the two models can be directly compared to test for significance. Across all measures of fit, the hypothesized model is the superior model. Additionally, the chi-square difference test was significant, indicating that it is a statistically superior model. Table 3 shows the results of this analysis.

<table>
<thead>
<tr>
<th>Table 3. Baseline Versus Hypothesized Model Comparison Results</th>
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<tbody>
<tr>
<td></td>
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<tr>
<td>Baseline model</td>
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<tr>
<td>Hypothesized model</td>
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</table>

Note. AIC is the Akaike information criterion, a measure of model misfit. Lower values indicate a better fitting model. BIC is the Bayesian information criterion, another measure of model of misfit. Lower values indicate a better fitting model. -2LL is the -2 log-likelihood and can be used to compare nested models via a chi-square test.

Now that the hypothesized model has been shown to be the preferred model, the independent variables can be formally tested. Hypothesis 2 argues that a positive relationship between OSE and course performance exists. After addressing the nonindependence in the data using multi-level model, this hypothesis was supported (β=1.75, F(1, 697)=8.08, p=0.0046). This indicates that as students are more engaged with the course, their performance increases. However, the interaction of OSE and assignment type was also significant (F(3, 697)=4.83, p = 0.0025), which indicates that the nature of the relationship between OSE and course performance depends on the type of assignment.
The data was split up based on assignment type and the relationship between OSE and course performance was tested again. These four tests show the impact of OSE on a particular type of assignment. When these analyses were conducted, OSE only had a significant impact on research paper scores and software project scores. OSE did not display a significant relationship with test scores or quiz scores, though the sign of the relationship was in the hypothesized direction. Table 4 contains the results of these tests.

<table>
<thead>
<tr>
<th>Tests</th>
<th>Research Papers</th>
<th>Quizzes</th>
<th>Software Projects</th>
</tr>
</thead>
<tbody>
<tr>
<td>F(df)</td>
<td>1.33 (1, 232)</td>
<td>10.33 (1, 232)</td>
<td>0.25 (1, 232)</td>
</tr>
<tr>
<td>β</td>
<td>0.22</td>
<td>0.35</td>
<td>0.06</td>
</tr>
<tr>
<td>p</td>
<td>0.2492</td>
<td>0.0015**</td>
<td>0.6142</td>
</tr>
</tbody>
</table>

*Note.* Values marked with ** are significant at α < 0.01.

**DISCUSSION**

This section explores the implications of our findings and offers recommendations for professors, advisors, and universities to mitigate the effects of computer anxiety and computer-mediated communication anxiety (CMCA) in online courses. Additionally, it addresses the study's limitations and suggests directions for future research.

**Discussion of the Impact of Anxiety on Engagement**

Grounded in Attentional Control Theory (ACT), which posits that anxiety hinders performance, this study developed several hypotheses to examine how two forms of anxiety and their interaction affect student engagement. The findings largely support these hypotheses. In the presence of a significant interaction, the main effects are not interpreted, as the interaction indicates that the predicted values depend on the levels of the other variable involved. This is evident from the simple slopes analysis results (see Figure 3). Although the directionality of an interaction is not typically hypothesized, some unexpected implications emerged.

The predicted values for online student engagement (OSE) were illustrated in a wireframe graph in Figure 2, showing a saddle-shaped interaction. The simple slope analysis examined the relationship between CMCA and OSE at high, medium, and low levels of computer anxiety. This analysis, represented in Figures 2 and 3, indicates that the relationship between CMCA and OSE varies depending on the student's level of computer anxiety.

ACT suggests that anxiety impairs performance, and in this context, it would impede course engagement. Contrary to the expectation that high levels of both CMCA and computer anxiety would lead to the lowest levels of engagement, and low levels of both anxieties would lead to the highest levels of engagement, the simple slopes analysis revealed a more nuanced picture.

For students with high computer anxiety, the relationship between CMCA and OSE is negative, as depicted by the yellow line in Figure 3. This suggests that these students are less likely to engage with the course material, leading to lower course performance, as hypothesized. However, the relationship changes for students with lower levels of computer anxiety.

Students with average or low computer anxiety exhibit a positive relationship between CMCA and OSE. In this scenario, higher anxiety about using a computer as a communication tool correlates with increased engagement with the course. This might be because these students, less anxious about using computers in general, engage more with the course content to avoid using the computer for communication, such as contacting the professor. Despite the persistent misconception that online students should not interact with their professors, this behavior can positively impact course performance (Broadbent & Howe, 2023). Future research should investigate whether students with low computer anxiety use alternative resources to engage with the course content. These findings can be summarized in Table 5.
Table 5. Summary of Study Findings

<table>
<thead>
<tr>
<th>Condition</th>
<th>Engagement Level</th>
<th>Possible Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>High computer anxiety + High CMCA</td>
<td>Low engagement</td>
<td>Students are overwhelmed by both anxieties, leading to disengagement.</td>
</tr>
<tr>
<td>Low computer anxiety + Low CMCA</td>
<td>Moderate engagement</td>
<td>Lower anxiety overall results in average engagement.</td>
</tr>
<tr>
<td>Low/average computer anxiety + High CMCA</td>
<td>Higher engagement</td>
<td>Students engage more with course content to avoid computer-mediated communication.</td>
</tr>
<tr>
<td>Low/average CMCA + High computer anxiety</td>
<td>Higher engagement</td>
<td>Students overcome anxiety about computer use by accessing necessary help for course tasks.</td>
</tr>
</tbody>
</table>

This study extends ACT by demonstrating that different types of state anxiety can interact, with some combinations potentially enhancing performance. This contrasts with the traditional view that anxiety uniformly impedes performance (Broadbent & Howe, 2023; Keeley et al., 2008; Lester et al., 2005; Thatcher & Perrewe, 2002).

To increase engagement, professors, advisors, and universities should adopt strategies tailored to address these anxieties. For technical courses requiring extensive computer use, incorporating gamification strategies with low-risk assignments can help reduce anxiety and build confidence. For students anxious about using computers as communication tools, providing multiple communication modalities can be beneficial. Advisors can recommend face-to-face classes for students anxious about computer-mediated communication when feasible or inform professors of students’ anxieties so they can offer additional support. Universities should also promote counseling services to help students manage their computer anxiety and CMCA. If computer mediated communication is the only option, telling the student that it is fine to turn off their webcam can help, though this can be detrimental in a group setting (Ramirez Perez, Ditta, & Soares, 2023).

Discussion of Engagement and Student Success

The fourth hypothesis examined the impact of course engagement on student performance, as measured by grades. The relationship between engagement and success varied by assignment type. Engagement did not significantly affect performance on proctored tests and open-book quizzes, which assess lower-order cognitive skills. However, engagement positively influenced performance on software projects and research papers, which require higher-order thinking skills such as critical evaluation, problem-solving, and strategic decision-making. These skills are highly valued by accrediting bodies (American Psychological Association, 2013; The Joint ACM/AIS IS2020 Task Force, Leidig, P., & Salmela, H., 2021).

Since engagement is important to success on these types of assignments, it is important to understand how to increase student engagement. According to Dixson (2010, 2015), creating connections is the primary driver of how a professor can encourage and get students to engage with course content. Connections for students to interact with each other are important, in an online course, this often means discussion boards. More than course discussion boards, professors can encourage students to interact outside of normal course channels. Informal connection opportunities, powered by technologies outside of the formal university technology stack such as GroupMe, also can play a role in increasing student engagement. These informal channels that the professor is not a part of, are also ways for students to create connections and thereby increase their engagement.

Other methods to increase engagement are to use instructional games, which has been shown to increase engagement, understanding, and test scores (Baszuk & Heath, 2020; Çakiroğlu, Baş büyük, Güler, Atabay, & Memiş, 2017). However, online instructional games like Kahoot can trigger computer anxiety, thereby preventing those who are anxious about using a computer from gaining those benefits that come with course engagement. If professors can identify those students who have computer anxiety, campus counseling centers can work with those students to help
them overcome their computer anxiety. Exposure therapy has a long history dating back over a century in treating state anxieties (V. M. Brown, Price, & Dombrovski, 2023).

Professors should encourage both formal and informal interaction channels, as these enhance students' perception and performance in the course (Baranik, Wright, & Reburn, 2017). Concerns about cheating in informal communication networks like GroupMe appear to be unfounded, as students reported using these platforms mainly for sharing helpful tips and information, rather than answers.

Online courses inherently require extensive computer use, which can trigger computer anxiety. CMCA can further inhibit communication between students and professors. Effective course design can enhance engagement (Tualatulelei, Burke, Fanshawe, & Cameron, 2022), but may require adjustments for students with computer anxiety or CMCA to be truly effective.

STUDY IMPLICATIONS

In terms of mitigating the effects of computer anxiety and CMCA in online courses, the study suggests several practical recommendations for educators and institutions. First, the interaction between CMCA and computer anxiety suggests that a tailored approach to student engagement could be beneficial. For instance, students with high computer anxiety may benefit from personalized support and anxiety-reducing strategies offered by campus counseling centers. Advisors would also want to encourage these students to focus on taking face to face classes. Conversely, those students with lower computer anxiety could become more engaged if the professor were to incorporate instructional games into the course (Baszuk & Heath, 2020; Çakıroğlu et al., 2017).

The impact of course engagement and performance also carry implications as well. Since engagement was not related to performance for lower order learning assessments, professors can be strategic in how a course is designed. Not every assessment needs to tap into higher-order learning. If students need to remember or understand concepts, being deeply engaged with the course is less important. However if students need to critically evaluate options and make complex decisions, the content leading up to those assessments needs to be more engaging.

STUDY LIMITATIONS & FUTURE DIRECTIONS

No study is perfect, and there are several possible concerns with this study. First, the course selected to use for this study was a single course at a single university. The course was an overview management information systems (MIS) course required for all business majors. The university where the data was collected does not offer a MIS degree, so many students begin the course with a “why do I have to take this class” mindset and view the course simply as a box to check off on their way to graduation. Generalizing these results to other situations where students may arrive more cognitively primed to engage with the material (e.g., in courses in their major) may not be warranted. It stands to reason that the effects between engagement and performance would be even more pronounced in this situation. The interaction of anxiety on engagement could be different depending on the course. Future research should investigate the generalizability of these findings. Additionally, future research should investigate the role of personality, particularly introversion and extraversion, on the generalizability of these findings. One line of thought surrounding introverts and online interactions argues that they can become more interactive in an online setting because they are interacting away from a group of others in an online environment (Abe, 2020; Al-Dujaily, Kim, & Ryu, 2013). Another line of thought argues that individuals who have better social skills will use these skills to great effect in discussion boards, whereas individuals who are less socially adept are likely to gain less from their online interactions (Amichai-Hamburger & Etgar, 2019; Cheng, Wang, Sigerson, & Chau, 2019).

Second, there could be response bias because providing course performance data was optional. Most participants did opt in to share their course performance data, but there were also a sizable number of students who chose not to participate at all. To address this valid concern, t-tests were conducted where the students who shared their performance data were compared to those who either did not share or did not participate. None of these t-tests showed any significant difference between the means on the assignments for either group, so there does not appear to be a response or selection bias in the study sample.
Third, there could be an attenuating effect of continued online learning on anxiety. As a student continues to take online courses, they will have repeated interactions with technology, and successful interactions could alleviate the anxiety the student originally felt. Both CMCA and computer anxiety are state anxieties meaning an individual only feels anxious when in the presence of the anxiety causing stimulus. Exposure treatments for state anxiety have been effectively used, where an individual is exposed to the anxiety provoking stimulus and new information which is incompatible with the anxiety response is incorporated, i.e., a computer anxious individual successfully uses a computer and continued success leads them to overcome their anxiety (Finn, Sawyer, & Schrot, 2009; Holtz, Hamm, & Pané-Farré, 2019). However, when this has been successfully reported in the literature, it was based on a carefully crafted protocol designed to overcome the anxiety. A student who just keeps enrolling in online classes employing a “fake it ’til you make it” strategy and with enough attempts they will “get the hang of online learning” is unlikely to be unsuccessful.

Lastly, this sample was collected during the COVID-19 pandemic when online courses were the only courses being offered by the university. Future research should replicate these findings in a more traditional learning setting. In a face-to-face class, when a student can directly interact with the professor, does CMCA still play a role in engagement? It may because students often interact with their professors well outside of normal class or office hours. However, many students are opting to take online courses while living in the on-campus dorms and universities offering required courses exclusively online, the issues discussed in the paper are not limited to historic events such as the COVID-19 pandemic as students are staying online.

CONCLUSION

This study investigated the impacts of computer anxiety and computer-mediated communication anxiety on student engagement with course material, and how their engagement with material impacted their course performance. The two types of anxiety interacted where the absence of one type of anxiety allowed a student to address the other or otherwise engage with the course, and to succeed in the course. Because online courses are only going to continue to grow, identifying and helping students engage with course material is important, even after the COVID-19 pandemic is over and things return to “normal.” This study makes important contributions to the role anxiety plays in course performance and offers several actionable suggestions professors, advisors, and universities can implement to help students succeed in their online classes.

REFERENCES


APPENDIX: MEASUREMENTS

Computer Anxiety (Lester et al., 2005). 7-point Likert Anchors: Strongly Agree—Strongly Disagree
1. I feel confident and relaxed while working on a computer
2. The harder I work at learning computers, the more confused I get
3. I sometimes feel that computers do not like me
4. I have always had problems working on computers
5. I can usually manage to solve computer problems by myself

Computer-Mediated Communication Apprehension (Scott & Timmerman, 2005). 7-point Likert Anchors: Strongly Agree—Strongly Disagree
1. I look forward to the opportunity to interact with others on the computer
2. Although I speak fluently with friends, I am at a loss for words when interacting online
3. I always avoid communication via computer if possible
4. I feel that I am more skilled than most others when interacting with people online
5. I dislike having to limit my communication to whatever is possible on a computer
6. I am afraid to voice my opinions when interacting with others on the computer
7. I would enjoy giving a presentation to others online
8. I look forward to expressing myself during online meetings
9. I am afraid to express myself in group discussions online
10. I like to get involved in computer-based group discussions

Online Student Engagement (Dixson, 2015). 7-point Likert Anchors: Not at all characteristic of me—Very characteristic of me
1. Making sure to study on a regular basis
2. Putting forth effort
3. Staying current on the readings
4. Looking over class notes between getting online to make sure I understand the material
5. Taking good notes over readings, PowerPoints, or video lectures
6. Reading the text carefully
7. Applying course material to my life
8. Finding ways to make the course interesting to me
9. Helping fellow students
10. Getting a good grade
11. Getting to know other students in the class

Coping (Holahan & Moos, 1987). 5-point Likert Anchors: Does not describe me—Describes me extremely well
1. When dealing with a problem, I spend time trying to understand what happened.
2. When dealing with a problem, I try to see the positive side of the situation.
3. When dealing with a problem, I try to step back from the problem and think about it from a different point of view.
4. When dealing with a problem, I consider several alternatives for handling the problem.
5. When dealing with a problem, I think about what it might say about bigger lifestyle changes I need to make.

Self-control (Tangney et al., 2004). 7-point Likert Anchors: Strongly Agree—Strongly Disagree
1. I am good at resisting temptation
2. I have a hard time breaking bad habits
3. I refuse things that are bad for me
4. I wish I had more self-discipline
5. Pleasure and fun sometimes keep me from getting work done
6. I have trouble concentrating
7. I am able to work effectively toward long-term goals
8. People would say that I have iron self-discipline
E-propinquity (Walther & Bazarova, 2008). 8-point semantic differential
Please select how accurately each adjective pair describes your interaction with the professor. When thinking about your interactions with the professor, consider email interactions, video interactions, audio interactions, Zoom interactions, and Microsoft Teams interactions.

1. Distant—Nearby
2. Close—Far
3. Together—Separate
4. Proximal—Remote
5. Disconnected—Connected
6. Adjacent—Far away
7. Inaccessible—Accessible

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