COMPUTER ANXIETY, COMPUTER SELF-EFFICACY, AND COMPUTER EXPERIENCE: PREDICTION OF PERFORMANCE AND ENGAGEMENT IN ONLINE COLLEGE STUDENTS

by

Beverly Pyle Barrett

JOHN HINTON, PhD, Faculty Mentor and Chair

ALISA ESTEY, PhD, Committee Member

LANA RIGGINS SAMPSON, PhD, Committee Member

Elizabeth Riley, PhD, Dean

Harold Abel School of Psychology

A Dissertation Presented in Partial Fulfillment

Of the Requirements for the Degree

Doctor of Philosophy

Capella University

August 2018

Abstract

The study was designed to examine the relationship among computer anxiety, computer self-efficacy, computer experience, performance, and engagement. Previous research has demonstrated that these topics are related; however, few studies have included all of these variables. Specifically, this study was designed to answer the following research questions: Do scores on measures of computer anxiety, computer self-efficacy, and computer experience predict successful course completion of a general education course in online community college students?; and Do scores on measures of computer anxiety, computer self-efficacy, and computer experience predict course engagement in a general education course in online community college students? The impact of gender and academic major upon these predictions was also evaluated. A quantitative, non-random, non-experimental research design and a non-probability, convenience sample were utilized to address the research questions. The sample included 108 participants with the majority being female and pursuing a career in the health care field. Binary logistical regression and multiple linear regression were performed to analyze the data. Results indicated that no significant relationship existed between the predictor variables and performance and the null hypothesis was retained. The multiple linear regression revealed that computer anxiety, computer self-efficacy, and computer experience did predict engagement, $F(5, 34) = 2.79$, $p = .03$. The regression model further revealed that when the other variables were controlled, computer anxiety was a significant predictor of engagement. Limitations of the current research design are discussed along with recommendations for future research.

Dedication

This dissertation is dedicated to my parents, Bro. Texil and Mary Pyle, who instilled in me an appreciation for education and learning and my brother, Dr. William Pyle, who has encouraged and challenged me through my educational journey. Bub, you challenge me to think more deeply about many topics and I love our talks (even when, maybe especially when, we disagree!).

Also, to my husband and sons who have endured my crazy schedule without complaint. Marty, you are always standing with me and supporting me whatever I pursue. You never hesitated when I wanted to further my education and simply said, “We’ll figure it out and make it work.” I love you! Greg and TR, I am so proud to be your mom. It is my greatest life pursuit and I can’t wait to see where life takes you. I love you guys with all my heart!

Last, but not least, to God who has blessed me with amazing opportunities both personally and professionally.

Acknowledgments

My journey has been filled with many individuals who had a role, directly and indirectly, in my completion of this dissertation:

- Psychology faculty at Murray State University who encouraged and instilled in me a love for the discipline. Especially Dr. Joel Royalty and Dr. Alyssa Ritter who introduced me to the world of statistics and research.
- Dr. John Hinton who has been supportive and encouraging throughout this process. Thank you for your feedback and the effort you have devoted to my education.
- Dr. Alisa Estey and Dr. Lana Riggins Sampson, my committee members, for your input and time invested in me.
- The psychology faculty at Capella University who have challenged me in my pursuit of knowledge. Specifically, my research colloquia instructors, Dr. Louis Kavar, Dr. Angela Bruch, and Dr. Bruce Fischer, your assistance was invaluable.

Table of Contents

List of Tables

CHAPTER 1. INTRODUCTION

Background of the Problem

Although modern society has become increasingly technology-oriented during the last few decades, 30-40% of people experience some form of computer anxiety (Buche, Davis, & Vician, 2007). Many assume that younger generations are more comfortable with computers; however, research indicated that college students still report high levels of computer anxiety (Saadé & Kira, 2009). This indicates that simple exposure to technology and computers does not guarantee individuals will feel comfortable with them. Given the increased popularity of online courses and the high drop-out rates of adult learners (Park & Choi, 2009), it is critical that barriers to successful completion of education be examined.

Academic success has been linked to student engagement in the classroom. Engagement refers to the degree to which the student is actively participating in the learning process (Bilge, Tuzgol Dost, & Cetin, 2014). Empirical evidence has shown that engagement is associated with dropout rates and academic achievement (Hirschfield & Gasper, 2011). Additionally, high levels of self-efficacy have been shown to be related to high levels of engagement in the classroom (Bilge et al., 2014). Compeau, Higgins, and Huff (1999) also found that computer self-efficacy impacted behavioral reactions to technology. The implication for online education is that the level of engagement and performance may be affected by students' confidence in their ability to complete the tasks, which is consistent with social cognitive theory (Bandura, 1989), since self-efficacy has demonstrated a positive correlation with motivation levels and task persistence (Bandura & Cervone, 1983).

Potential barriers to successful academic performance may be one's level of computer anxiety, computer self-efficacy, and computer experience. Computer anxiety refers to feelings of discomfort, nervousness, avoidance, and even physical symptoms when thinking about or actually interacting with computers (Fuller, Vician, & Brown, 2006). Beckers and Schmidt (2001) investigated computer anxiety using factor analysis and identified six underlying dimensions: computer literacy, self-efficacy, physical arousal caused by computers, affective feelings about computers, beliefs about the benefit of computers, and beliefs about dehumanizing effects of computers. Computer self-efficacy has been defined as one's perceived ability to perform computer tasks or learn new skills (Marakas, Yi, & Johnson, 1998). Computer experience refers to already established computer skills that an individual possesses. Specifically, research has revealed that computer self-efficacy and computer experience are closely linked to computer anxiety (e.g., Brosnan, 1998; Fagan, Neill, & Wooldridge, 2004).

There is evidence that computer anxiety negatively effects performance in a variety of settings. This has been demonstrated in an introductory statistical course (Abd-El-Fattah, 2005), in a specific task performance in a computer programming course (Vician & Davis, 2003), and a database task (Brosnan, 1998). Brosnan's research (1998) found that high levels of computer anxiety were associated with more errors, and multiple regression analysis revealed that computer self-efficacy explained 39% of the variance in performance. For online students enrolled in general education courses, this means that their feelings of discomfort, or computer anxiety, and their perceived abilities, or computer self-efficacy, could impact their performance on computer-related tasks necessary to complete coursework.

Although computer self-efficacy negatively correlates with computer anxiety and positively correlates with computer experience (Fagan et al., 2004), simply increasing exposure to computers may not increase performance. The type of previous experience with computers is important to consider. There is empirical evidence that confidence using the internet did not convert into computer self-efficacy (Sam, Othman, & Nordin, 2005). Just because one may use technology or a computer often does not mean that one will be confident in performing specific computer tasks or using specific programs, such as word processing, spreadsheets, or databases.

Statement of the Problem

Existing Literature

Although modern society has become increasingly technology-oriented, 30-40% of people experience some form of computer anxiety (Buche et al., 2007). Many assume that younger generations are more comfortable with computers; however, research indicated that college students report high levels of computer anxiety (Saadé & Kira, 2009). Additionally, nearly half of a sample of older children and adolescents reported moderate to high levels of computer anxiety (Deryakulu & Caliskan, 2011). Empirical evidence has revealed that confidence using the internet does not convert into computer self-efficacy (Sam et al., 2005). Computer self-efficacy negatively correlates with computer anxiety and positively correlates with computer experience (Fagan et al., 2004). Research on the impact of computer anxiety on performance documented negative impacts on performance in a variety of situations, such as an introductory statistical course (Abd-El-Fattah, 2005), specific task performance in a computer programming course (Vician & Davis, 2003), and a database task (Brosnan, 1998).

Gap in the Literature

The research literature on computer anxiety indicates that we know it negatively impacts performance on computer specific tasks (Abd-El-Fattah, 2005; Brosnan, 1998; Vician & Davis, 2003); however, we do not know how it impacts performance in general education courses in which the computer skills are auxiliary and not content-related. The literature review reveals a gap in the association of these variables with course performance and engagement of community college students.

Purpose of the Study

The purpose of this study was to identify levels of computer anxiety, computer self-efficacy, and computer experience in online community college students and whether these variables predict performance and engagement in an online general education course. It is important to student success for any barriers to be correctly identified and solutions sought. The published literature will be reviewed in a more detailed fashion in Chapter 2, along with a critique of the research. This current research examined these topics simultaneously in a unique context, namely in a community college population of online general education students. The results of this study could add to the body of knowledge regarding barriers to success in online education and could be used by colleges and universities to implement programs that would assist students to be successful. For instance, Fagan et al.'s research (2003) found that students with higher levels of computer anxiety spent more time in the computer lab, which may have indicated that students scoring higher in computer anxiety required additional time to complete computer tasks.

Significance of the Study

The research was designed within the parameters of logical positivism (Burgos, 2007) and social cognitive theory (Bandura, 1989). It furthers social cognitive theory by providing new information about the predictive nature of a specific anxiety, specific self-efficacy, and experience on performance. This was accomplished through an objective investigation of the concepts using accepted research methodology and design as supported by logical positivism (Burgos, 2007). General psychology has been interested in evaluating and advancing theory and the objective examination of phenomena (Burgos, 2007). This research may provide new knowledge about the interaction of personal factors, such as computer anxiety and computer self-efficacy, on performance behavior in an online community college environment which contributes to triadic reciprocal causation of Bandura's social cognitive theory (Bandura, 1989).

Practical implications of this research may include providing new knowledge to college administrators to help alleviate these barriers to online education for students. Administrators may benefit from additional knowledge about factors that impact success for online students which may lead to improved procedures or services to benefit the students. The community at large may be improved by the presence of a better educated workforce. Additional research in this area had been recommended by many authors, including Buche et al. (2007), Lee and Huang (2014), and Smith and Caputi (2001). Specifically, this research could contribute to the development of orientation programs for new online students to become familiar with the course management program. Online students may benefit from ongoing training in any new applications or programs that will be required of them.

Research Questions

Research Question #1

Do scores on measures of computer anxiety, computer self-efficacy, and computer experience predict successful course completion of a general education course in online community college students?

Subquestions

- Do males and females differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict successful course completion of a general education course in online community college students?

- Do participants from different majors differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict successful course completion of a general education course in online community college students?

Research Question #2

Do scores on measures of computer anxiety, computer self-efficacy, and computer experience predict course engagement in a general education course in online community college students?

Subquestions

- Do males and females differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict engagement in a general education course in online community college students?

- Do participants from different majors differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict engagement in a general education course in online community college students?

Definition of Terms

Computer anxiety refers to feelings of discomfort associated with working with or thinking about working with computers. This is a construct that can vary between individuals as evidenced by the variety of instruments that have been developed and used to measure it, for example, the Computer and Technology Use Scale (Conrad & Munro, 2008), the Information Technology Anxiety Scale (López-Bonilla & López-Bonilla, 2012), and the Computer Anxiety Rating Scale (Raub, 1982). There are also numerous published research studies which have measured and explored this construct (e.g., Celik & Yesilyurt, 2013; Deryakulu & Çalışkan, 2012; Desai, 2001). In the current study, computer anxiety was measured using the Computer Anxiety Scale (Wild et al., 2012a).

Computer self-efficacy has been used to refer to one's confidence in one's ability to be successful and is context specific (Bandura, 1989). This construct has been shown to vary between individuals and between tasks and situations (Compeau & Higgins, 1995; Marakas et al., 1998). Multiple instruments have been developed to measure computer self-efficacy (e.g. Compeau & Higgins, 1995). Computer self-efficacy has been researched in a variety of populations, such as Unimas undergraduates (Sam et al., 2005), teacher candidates (Shapka & Ferrari, 2003), and management information systems upperclassmen (Hauser, Paul, & Bradley, 2012). Marakas et al. (1998) conducted a meta-analysis of over 40 published articles on computer self-efficacy. In the current study, computer self-efficacy was measured using the Computer Self-Efficacy Scale (Compeau & Higgins, 1995)

Computer experience refers to one's previous exposure to and current ability to use computer programs. Individuals can vary in the number of programs to which they have been exposed and their degree of ability to use these programs (Bozionelos, 2004b). This is demonstrated in the published literature by the development of instruments to measure the construct (Bozionelos, 2004a; Kay, 1993) and in the number of research articles which include computer experience as a variable (Bozionelos, 2001a; Fagan et al., 2003; Kay, 1993). In the current study, computer experience was measured by a short three question survey developed for this research project.

Engagement in the classroom refers to the degree to which a student is actively participating in the learning process. This varies between individuals and numerous research articles have been published about this topic (e.g., Guthrie & Clauda, 2013; Hirschfield & Jasper, 2011; Spence & Usher, 2007). Engagement in this study was measured using the Online Course Impressions Instrument (Keller & Karau, 2013a).

Performance is a measurement of how well the student performed academic tasks. It was measured by grade received in an online course the previous semester. Participants provided a self-report of their grade.

Research Design

The research questions were answered using a quantitative, non-random, non-experimental research design and a non-probability, convenience sample. The methodology was quantitative, since the variables were measured on a numerical scale (Warner, 2013).

A non-random design was utilized since participants were recruited based upon their enrollment in an online general education course. This design was appropriate to answer the research questions because students were self-selected and could not be randomly assigned to groups, which would be required for an experimental design. The sampling strategy was non-probability, since all online community college students did not have an opportunity to participate. A convenience sampling design was used since the volunteers invited to participate were those enrolled in the community college to which the researcher had access. An analysis with G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) was performed based upon power = .80, alpha = .05, and a medium effect size which indicated that a sample size of 77 was needed for this study.

Volunteers were recruited through their online courserooms and invited to complete an online survey via Qualtrics. The survey included sections measuring demographic information, computer anxiety, computer self-efficacy, computer experience, engagement, and performance. The relationship of the predictor variables to the outcome variables was evaluated using binary logistic regression and multiple linear regression.

Assumptions and Limitations

Assumptions

The current research project utilized a quantitative research methodology which embodies certain assumptions. According to Davis (2009) the assumptions of quantitative methodology are positivism, operationalism, reductionism, mechanism, and objectivity. Positivism is the belief that reality is objective (Brand, 1996) and is revealed through quantitative research methods, including internal states (Burgos, 2007). Operationalism is supported by establishing specific definitions of concepts during the design phase, including how they will be measured. Reductionism implies parsimony is used by employing the simplest explanations. Mechanism suggests that interactions between concepts are guided by logical causal laws.

Lastly, objective methods should be utilized to remove the influence and opinions of the researcher.

Certain other assumptions are inherent to the research methodology. First, the research design can answer the stated research questions. Non-experimental research designs are widely accepted as appropriate in this area of interest (i.e. Fuller et al., 2006). Another assumption is that internal states can be adequately measured using surveys. Numerous studies (e.g., Lee & Huang, 2014) support the popularity of using surveys to measure the constructs included in this research. Lastly, it is assumed that these constructs are adequately measured by the instrument used. The validity and reliability data on the various instruments described in the Methodology chapter supports that this assumption is met.

Limitations

The research design used had its strengths, such as allowing the examination of constructs that might be unethical or impractical to study using experimental designs; it also had its limitations that must be recognized. For example, non-experimental designs preclude any inferences of causation between the variables (Warner, 2013). Due to using convenience sampling, participants may not have been representative of the college student population and no manipulation of variables occurred. Although the survey format has often been used, there was the possibility that participants did not provide accurate information, which may have skewed the data. Lastly, measuring computer anxiety via an electronic survey may have resulted in participant self-selection, specifically, that those volunteers who were not comfortable with computers may have chosen not to participate.

Despite these limitations, this research design was appropriate for this topic. Participants could not be randomly assigned to groups due to examining pre-existing personal factors, such as anxiety, self-efficacy, and experience. While causation could not be inferred the relationship between the variables could still be investigated. Faulty memory or positive self-presentation may have influenced data in the self-reported surveys; however, evidence suggested that self-reported ratings were comparable to ratings by others (Vazire & Mehl, 2008). As mentioned previously, computer use for a specific task, such as a database search or formatting a document, was not comparable to internet or other technology use (Sam et al., 2005). Therefore, selecting answers on a survey may have been a more familiar task and may not have been as intimidating as having to navigate an online courseroom or prepare documents for participants.

Organization of the Remainder of the Study

The next section of this paper includes a literature review. This segment includes a description of the methods of searching, a review of the published literature that provides the theoretical underpinnings as well as the basis of current knowledge of computer anxiety, computer self-efficacy, and computer experience, and a critique of the previous research. Chapter 3 will provide methodological details, such as the research questions, hypotheses, research design, population and sample. The procedures will also be outlined including the participant selection, data collection, analyses, and instruments used. This section will also state any ethical considerations and how they were addressed. Chapter 4 will present the results from the present study including a description of the sample and hypothesis testing. Finally, chapter 5 will provide a discussion summarizing the results and any conclusions which may be derived from these results along with limitations of the study. Implications for practice and recommendations for further research will also be presented.

CHAPTER 2. LITERATURE REVIEW

Methods of Searching

A comprehensive search was conducted to investigate the current knowledge available regarding computer anxiety, computer self-efficacy, computer experience, performance and engagement of online students. Several databases were utilized including Computers and Applied Sciences Complete, Dissertations @ Capella, Dissertations and Theses Global, Education Research Complete, ERIC, Proquest Psychology Journals, PsycArticles, and PsycInfo. The research topic was interdisciplinary, therefore, it required searches in the disciplines of technology, education, and psychology.

A variety of search terms were employed for each concept. Initially, a search was conducted on factors associated with success in online education which led to an interest in computer anxiety and computer self-efficacy. A systematic search was initially used to investigate these concepts. *Anxiety*, *self-efficacy*, *performance*, and *engagement* were investigated in general. A subsequent search focusing on computers was conducted, including *computer anxiety*, *computer self-efficacy*, and *computer experience*. Further searches were completed substituting the term *technology* for *computer*. As the literature review revealed that computer use and technology use differed, it became necessary to explore both terms and focus on the operational definitions to distinguish research that was applicable to the current topic. *Computer literacy* was also investigated since it has been used synonymously with computer experience.

Online learning performance and *student engagement* were also researched. Other terms, such as *distance learning*, *computer-aided learning*, and *online education* were examined as well. Student engagement was also investigated using the phrases *student satisfaction* and *student success*. Additionally, student was replaced with *learner* for searches.

The theoretical foundation for this research was conducted using a variety of search terms. A search was performed for *social cognitive theory* and *logical positivism*. In addition, a search was conducted for the terms *positivism*, *theoretical foundations*, and *theory*. All of the aforementioned terms were all examined individually and in combination. Searches were conducted using these terms and phrases in dyads and triads. Some of these terms were added as the literature indicated potential connections.

Theoretical Orientation for the Study

A theoretical foundation, or perspective, is the guiding viewpoint for research. This theoretical foundation will determine what topics are appropriate to study, how they are investigated, and how the data will be collected and then analyzed. The theoretical foundation for the current research project was logical positivism and the specific theory was social cognitive theory.

Logical Positivism

Logical positivism has been a leading perspective in psychology since the early 1900s (Brand, 1996; Burgos, 2007). The logical positivism viewpoint values theoretical explanations for observed phenomena (Hergenhahn & Henley, 2014), and it espouses that an objective reality exists (Brand, 1996) and can be measured (Burgos, 2007). Knowledge about this objective reality is possible through strict research methods and replication, which should remove all subjective opinions and experiences that may lead to error (Burgos, 2007). In summary, the main tenets of logical positivism are: a single objective reality, that knowledge about reality can be measured, that only objective reality is valuable, and that valuable knowledge comes from quantitative research methods.

The investigation of the mediating influence of internal states, such as anxiety and self-efficacy, upon performance falls within the logical positivism perspective. Logical positivism values both observable constructs, such as behavior/performance, and unobservable constructs that can be measured in other ways, such as emotional states and cognitions (Burgos, 2007). Anxiety and self-efficacy are internal states which can be measured through behavioral cues or self-report measures. The underlying tenets of logical positivism are represented in social cognitive theory (Bandura, 1989), which was the basis for this research project.

Social Cognitive Theory

Bandura's social cognitive theory (1989) stated that individuals are autonomous agents and that internal factors within a person interact with the external environment to impact behavior. Behavior then, in turn, influences the environment. The importance of the interaction between personal factors and the environment (Geiser et al., 2015) has been researched in a variety of areas, such as decision making in a simulated organization (Wood & Bandura, 1989) and the effects of third party observers (Horwitz & McCaffrey, 2008). According to Bandura (1989) there was a "triadic reciprocal causation" (p. 1175) between the person, environment, and behavior. This was evident in the relationship between the person (computer anxiety, computer self-efficacy, and computer experience), the online educational environment, and performance (which is a behavior).

Social cognitive theory was previously called social learning theory (Bandura, 1977b). Behavioral learning theories emphasized the impact on behavior of an association between external stimuli, but social cognitive theory stated that expectation, a cognitive component, was also critical (Bandura, 1977b; Bandura, 1986). Bandura (1977b) has stated "Humans do not simply respond to stimuli; they interpret them" (p. 59). Early research on operant behavior by Baron, Kaufman, and Stauber (1969) showed that behavior was influenced by the type of instruction given, not just by the actual consequences experienced. In this series of experiments participants were either given instructions regarding reinforcement schedules or no instructions were provided. Similarly, some participants received feedback during the tasks and other participants did not receive feedback. Results indicated that response rates progressed in an orderly fashion for those receiving instructions regardless of feedback condition (Baron et al., 1969). However, those who did not receive feedback tended to establish poor response patterns in earlier trials and did not significantly improve when given the instructions later in the experiment.

Bandura (1977b) has stated that individuals form expectations about the consequences of future behavior from past experiences and use these expectations to choose between various possible actions. The information gained from experience provides information about oneself and task demands (Bandura, 1986), which is then used as one considers the possible outcomes of these alternate action plans (Bandura, 1997). Bandura (1997) has further suggested that success is more likely for individuals with more options available to them.

As actions are chosen and implemented, the environment is being dynamically created. Per Bandura (1997) "social structures…are created by human activity" (p. 6). As this concept was applied to the current research topic, it suggested that the online learning environment would be fluid and the specific cohort of students would create their own unique environment. The environment "will be changed to some extent by the behavior of the people in it" (Funder, 1991). Therefore, the learning environment would be formed as the students interact with each other and that specific learning environment. The actions of each student would be influenced by previous experience and his or her own personal levels of computer anxiety and computer self-efficacy.

Self-efficacy. Self-efficacy is one's perceived ability to cope with situations or successfully complete tasks (Bandura, 1977a). Social cognitive theory claimed that the efficaciousness of one's mindset would impact behavior (Bandura, 1997) and this has been well-documented (Bandura, 1977a; Bandura, 1982; Bandura & Cervone, 1983; Bandura & Locke, 2003). Self-efficacy can either enhance performance or hamper it (Bandura, 1989). When underlying skills or past performance was controlled, self-efficacy has been shown to be a significant predictor of later behavior (Locke, Frederick, Lee, & Bobko, 1984). This was particularly true for moderate to difficult goals compared to those goals perceived as easy or impossible (Locke et al., 1984). One's perception and interpretation of challenges may impact performance, especially behaviors related to motivation and persistence.

Evidence has suggested that higher self-efficacy leads to an increase in motivation (Bandura & Cervone, 1983) and to more persistence when faced with challenges (Bandura, 1977a). In fact, individuals may persist to receive an expected reward in the future even when current experiences are unpleasant (Bandura, 1977b). Beesley et al. (2010) identified persistence with challenging tasks as an important factor of educational engagement. This evidence suggested that self-efficacy may be an important factor in online students' motivation to complete tasks, particularly those perceived as challenging. In fact, research has demonstrated that task completion was influenced by whether there was a perception of threat or not (Sussman, Szekely, Hajcak, & Mohanty, 2016).

These studies (Beesley et al., 2010; Sussman et al., 2016) supported Bandura's (1986) assertions that those with low self-confidence would not persist. Bandura's self-efficacy theory suggested that individuals would undertake only those tasks which are evaluated as potentially successful (Bandura, 1977a). He has further stated that a task would be avoided even if associated with a successful outcome if there were doubts about one's ability to execute the required task (Bandura, 1986).

Self-efficacy has been shown to be domain-specific (Beelsey et al., 2010; Tay, Ang, & Van Dyne, 2006) and has been studied in several domains. For example, Spence & Usher (2007) investigated three specific self-efficacies in a single study – mathematic self-efficacy, computer self-efficacy, and self-efficacy for self-regulated learning. Examining self-efficacy within a specific domain was beneficial since confidence in one's ability to be successful may differ between domains.

A positive relationship between self-efficacy and performance has been demonstrated within academic settings. For example, González, Fernández, and Paoloni (2017) found that better performance was associated with higher levels of self-efficacy in Spanish students. Pouratashi, Zhub, Mohammadi, Rezvanfara, & Hosseinia (2013) found similar results with Iranian agricultural students.

Anxiety. An identified component of self-efficacy was physiological arousal (Bandura, 1977b) which includes anxiety responses. According to Bandura (1989) emotional responses would influence performance both directly and indirectly through cognitive processes. The connection between anxiety and self-efficacy has been studied in many areas, including avoidant behaviors (Bandura, 1989). Avoidant behaviors, such as procrastination or incomplete assignments, may be related to poor student performance. Specifically, in an online learning environment computer anxiety may lead to increased procrastination and incomplete assignments.

The physiological arousal when experiencing anxiety and its impact on performance has been studied for decades. It has been widely accepted that the relationship between arousal level and performance would reveal an inverted U shape (Hebb, 1955). Schlosberg (1954) summarized findings that demonstrated benefits of moderate levels of arousal, with both low and high levels associated with declines in performance.

High levels of anxiety can negatively impact performance; this includes specific anxieties in their related contexts. In an investigation on the impact of various anxieties on behavioral decision-making skills, Buelow and Barnhart (2017) found that three specific anxieties (math anxiety, physiological anxiety and test anxiety) predicted impaired decision-making. This negative impact on performance of high levels of anxiety has been documented in a variety of contexts including, but not limited to, academics (González et al., 2017; Pouratashi et al., 2013; Yadav & Sharma, 2013), athletics (Mabweazara, Leach, & Andrews, 2017), neuropsychological performance (Rezaei, Ramaghani, & Fazio, 2017), and executive functioning (Horowitz & McCaffrey, 2008).

The negative impact of high levels of anxiety on performance has been documented in a variety of academic situations and internationally. In an examination of academic success in teacher trainees, Yadav and Sharma (2013) found that a significant negative relationship between anxiety and achievement exists. In the context of a physics class participants scoring high in anxiety performed poorer than those with lower levels of anxiety (González et al., 2017). Test anxiety has been shown to be negatively correlated with academic performance in agricultural students (Pouratashi et al., 2013). These studies demonstrated the concern regarding the impact of anxiety on academic performance in multiple countries, such as India (Yadav & Sharma, 2013), Spain (González et al., 2017), and Iran (Pouratashi et al., 2013). Anxiety was included in a French scale designed to measure six emotions related to academics (Govaerts & Grégoire, 2008). Therefore, an interest in the impact of anxiety on academic performance is not unique to the United States.

A comparison of test anxiety in various settings provided support for social cognitive theory's assertion that situations would impact anxiety. Stowell, Allan, and Teoro (2012) assessed student emotions in a pretest-posttest design. There were three exam conditions – online at the student's choice of time and place, online at a designated time in a computer lab, or in a traditional classroom setting. Students reporting high levels of test anxiety in the classroom reported high levels in all conditions; however, those reporting low levels of test anxiety in a classroom reported significantly higher levels of test anxiety when taking the exam online. This emphasized the importance of context on emotional factors, such as anxiety.

Bandura's (1989) social cognitive theory fits well with this research topic. This theory explained how increased computer anxiety and decreased computer self-efficacy may negatively impact performance and how each of these would be impacted by experiences of success and failure. Additionally, this theory was helpful to describe how computer anxiety and computer self-efficacy can influence engagement behavior in an online course. The current research project fits within the social cognitive theory since it examined the predictive ability of a specific anxiety and a specific self-efficacy on the behaviors of performance and engagement.

Review of the Literature

The popularity of online education continues to rise and it is critical that educators understand the needs and barriers for learners. An ongoing examination of online education

(Allen, Seaman, Poulin, & Straut, 2016) revealed that participation in online education continues to increase each year. The latest reported data was from 2014 and indicated an increase of almost four percent in online education from the previous year. Additionally, one student in seven (14%) is enrolled exclusively in online courses and approximately one in four students (28%) is enrolled in at least one online course. This upward trend in online education has been seen over the 13 years in which this survey has been conducted (Allen et al., 2016). Allen et al. (2016) described enrollment trends in the United States, but this same trend has been seen internationally as well. For example, an investigation of an Australian marketing undergraduate online degree program revealed increasing online enrollment while face-to-face enrollment numbers remained consistent (Greenland & Moore, 2014). This body of research leads one to believe that online education will continue to be a significant component of the higher education system; therefore, understanding factors impacting student retention and success is vital.

It may seem logical to assume that those who choose online learning like computers and feel comfortable using them. However, liking computers does not appear to be a motivation according to the published literature. Fontenot, Mathisen, Carley, and Stuart (2015) investigated predictors of online learning enrollment in a group of marketing students. The main predictor of planning to take an online course was the quality of learning anticipated and the main predictors of online courses taken were scheduling and timing. This may suggest that other characteristics of online learning, such as flexibility, may appeal to learners. Many non-traditional students who may have additional outside demands, such as work, family, and finances are participating in online learning (Rovai, 2003) and the traditional learning environment may not be possible for them. Therefore, online learning may be chosen because it is the only viable option for continued education for these students.

Student retention and success has been studied from many angles. However, it is important to recognize that characteristics of online students may differ from face-to-face students. Rovai (2003) emphasizes differences in these populations, specifically, the increased presence of non-traditional students in online educational environments should be considered since this population already demonstrates increased drop-out rates (Rovai, 2003). It has been proposed that community colleges are a good fit for online courses (Liu, Gomez, Khan, & Yen, 2007), but the high drop-out rates for online courses is a concern. This supports the efforts to more fully understand the online student population especially in a community college.

Persistence amid adversity or challenging circumstances has been identified as a critical component to student retention in online learning (Park & Choi, 2009; Rovai, 2003). Success early in the educational experience may be a factor in later persistence. Greenland and Moore (2014) found significantly higher rates of student withdrawal in early introductory courses compared to higher level courses.

Similarly, Shea and Bidjerano (2016) found higher drop-outs rates in the first two years. This study was an annual comparison of community college students who had versus did not have online learning experience. At the end of a six-year observation period more of the online students had earned an associate degree or transferred. Additionally, they found that fewer of the online students earned a degree at the college where they initially enrolled, but were more likely to continue their education by transferring to another university and earning a bachelor's degree.

These studies regarding early drop-out rates (Greenland & Moore, 2014; Shea & Bidjerano, 2016) demonstrate the importance of early educational experiences for college students. Providing students with opportunities for success early in their academic careers may increase their self-efficacy which may lead to increased persistence when faced with challenges later in their educational journey.

This introduces the current topic of investigating how computer anxiety, computer self-efficacy, and computer experience relate to successful outcomes in online general education courses. These findings of online student behaviors can be explained by Bandura's (1989) social cognitive theory and its explanation of how anxiety, self-efficacy, and experience will impact student behaviors, such as performance and engagement in the online courseroom.

Performance and Engagement

Successful completion of academic goals is important for both students and administrators. As previously mentioned, approximately one-fourth of college students are enrolled in at least one online course and many are pursuing education exclusively online (Allen et al., 2016). Academic performance has been linked to the level of student engagement in the courseroom.

Student engagement can be predictive of future academic success and the likelihood of dropping out (Fall & Roberts, 2012; Hirschfield & Gasper, 2011). The published literature on engagement identifies three types of engagement – cognitive, behavioral, and emotional (Hirschfield & Gasper, 2011). Behavioral engagement included items such as tardiness, skipping class and completing assignments. Academic engagement included items related to completion of homework, attentiveness in class, and hard work. Emotional engagement included items related to school climate and bonding with teachers and peers. In a study of engagement and achievement in high school students, Fall and Roberts (2012) found that behavioral and academic engagement were positively correlated with academic success. Further findings from this research revealed that behavioral and academic engagement were negatively correlated with high school dropout rates. These results supported earlier research by Hirshfield and Gasper (2011) who found that behavioral and emotional engagement was associated with better outcomes. This body of research suggests that students who are actively engaged (behaviorally, academically, and emotionally) will be less likely to drop out and more likely to achieve academic success.

Since academic achievement is associated with student engagement, it leads one to wonder what factors can predict student engagement. Bilge et al. (2014) investigated factors associated with burnout and engagement in 605 students. They focused on the three factors - study habits, self-efficacy beliefs, and academic success. The results showed that students who scored higher in study habits as well as self-efficacy beliefs also scored higher in engagement. The burnout inventory used by these researchers had three subscales – exhaustion, cynicism and professional efficacy. The analyses indicated that lower scores on self-efficacy beliefs were linked with higher levels of exhaustion. Additionally, self-efficacy and academic performance were positively correlated.

Bilge et al.'s conclusions (2014) regarding exhaustion and low levels of self-efficacy supports the social cognitive literature, indicating that higher levels of self-efficacy are associated with higher levels of motivation (Bandura & Cervone, 1983) and increased persistence (Bandura, 1977a). Furthermore, it supports Beesley et al.'s earlier findings (2010) that a critical component of engagement is persistence with challenging tasks. These findings support that high self-efficacy is associated with higher levels of engagement and better academic performance which would lead one to believe that self-efficacy may be a predictor of engagement and academic performance.

Computer Anxiety, Computer Self-efficacy, and Computer Engagement

An important factor in student engagement and success in an online learning environment may be computer anxiety and computer self-efficacy. As stated previously self-efficacy is linked to engagement and performance in the classroom (Beesley et al., 2010; Hirschfield & Gasper, 2011). Therefore, computer self-efficacy may be critical to student engagement in an online courseroom and the level of student success. It has been established in the published literature (e.g., Shu, Tu, & Wang, 2011; Spence & Usher, 2007) that self-efficacy is contextual and should be studied within that context. Marakas et al. (1998) reviewed 40 previously published studies of computer self-efficacy to provide an integrated model. They state that "it requires a strong sense of efficacy to deploy one's cognitive resources optimally and to remain task-focused and goal-oriented in the face of repeated difficulties and failures" (Marakas et al., 1998, p. 158).

He and Freeman (2010) studied computer self-efficacy in 281 business students in order to understand how it develops and its impact on computer attitudes and intentions to focus in management and information systems in the future. Their results indicated that computer knowledge, computer experience, computer anxiety, and age were important in the development of computer self-efficacy. Also, computer self-efficacy was predictive of intentions to focus in management and information systems. This indicates that intention of future behavior is impacted by computer self-efficacy. For online students this may mean that computer self-efficacy would predict how engaged the student will be in an online courseroom.

In fact, research by Spence and Usher (2007) supported the connection between computer self-efficacy and engagement in an online mathematics courseroom. An examination of age, computer self-efficacy, computer playfulness, mathematics grade self-efficacy, self-efficacy for self-regulated mathematics learning, engagement, and performance was conducted with 164 students, 88 in a traditional classroom and 76 in an online courseroom. The online materials used by the online students were offered to the traditional students as supplemental material. Several findings were reported, but the result of interest for the current study is that computer self-efficacy was positively correlated with engagement with the courseroom for the online group; however, this link was not significant for their performance in the course. Performance was more closely linked to mathematics self-efficacy.

However, Hauser et al. (2012) found different results regarding performance and computer self-efficacy. In this research computer self-efficacy was measured in two forms, general computer self-efficacy and database-specific computer self-efficacy. General computer self-efficacy was closely linked with database-specific computer self-efficacy and both types of computer self-efficacy were positively related to performance for face-to-face and online students. Additionally, computer anxiety was shown to be associated with computer self-efficacy but not performance. Their model indicated that computer anxiety affects performance indirectly through computer self-efficacy.

Social cognitive theory has demonstrated the connection between anxiety responses and self-efficacy (Bandura, 1977b). This same connection has been seen in the literature for specific domains, such as computer anxiety and computer self-efficacy. Multiple studies (e.g., Saadé and Kira, 2009; Wilfong, 2006) have supported that computer anxiety is significantly related to computer self-efficacy. The interest in computer anxiety can be seen as early as 1969 when O'Neil, Spielberger, and Hansen investigated state anxiety on computer-assisted instruction, although these authors did not use the term computer anxiety. They measured state anxiety through a self-report measure and blood pressure readings during easy and difficult tasks. The results illustrated that during difficult tasks anxiety scores increased for all subjects; however, those in the high anxiety group made more errors during the difficult tasks compared to the easy tasks. While it is tempting to use the novelty of computers in the 1960s as an explanation for these findings, more current literature continues to document the negative impact of computer anxiety on performance in computer related tasks.

Interestingly, a comparison of computer anxiety between students with various business majors indicated that management and information systems students reported significantly less computer anxiety than those in other business majors, such as accounting, economics, finance, general business, management, and marketing (Havelka, Beasley, and Broome, 2004). Since an experimental design was not used causation cannot be inferred. Therefore, it is possible that the intense exposure to computers may have led to reduced computer anxiety or this major may have been more desirable to students with lower levels of computer anxiety. While comfort with computers may not be a factor for choosing online education, as discussed earlier, it may influence choice of major.

Beckers and Schmidt (2001) developed a model of computer anxiety which included six factors including computer literacy (i.e., computer experience), computer self-efficacy, physical arousal around computers, affective feelings about computers, beliefs about computer benefits, and beliefs that computers are dehumanizing. Their results indicated that computer literacy negatively impacted physical symptoms, such as shortness of breath and sweaty palms. Additionally, a positive connection between computer literacy and computer self-efficacy was found; however, there was no direct connection found between computer self-efficacy and physical arousal (specifically physical symptoms of anxiety) or affect. The authors suggested that computer self-efficacy impacts physical arousal indirectly through computer literacy.

Multiple investigations into the connection and interactions between computer anxiety, computer self-efficacy, and computer experience have been conducted. Fagan et al. (2003) administered a questionnaire to 978 undergraduate business students and found that computer anxiety was negatively correlated with computer self-efficacy and computer experience and that computer self-efficacy was positively correlated with computer experience. In this study the computer experience and computer usage were both measured. Computer usage was measured according to amount of time in the computer lab. Computer anxiety was found to be positively correlated with computer use indicating that students scoring higher in computer anxiety spent more time in the computer lab. The authors noted that a limitation of the study was the lack of information whether the computer lab use was required or not. If the computer use was required by an instructor then it would decrease the opportunity to avoid computer use and this finding may indicate that those scoring higher is computer anxiety may require more time to successfully complete tasks. An additional variable that was included in Fagan et al.'s (2003) study was technical support from the organization. The results indicated that technical support was positively associated with computer self-efficacy but unrelated to computer anxiety or computer usage.

More recent research has shown that computer self-efficacy mediates the influence of computer anxiety in an online learning environment. Saadé and Kira (2009) investigated computer self-efficacy and computer anxiety in online introductory courses for management information systems and information technology. The variables measured were computer anxiety, computer self-efficacy, and perceived ease of use of the learning management system. The findings revealed that computer self-efficacy has a strong positive relationship with computer anxiety and supported the hypothesis that it does mediate the impact of computer anxiety on the perceived ease of use. These results indicate that students with high computer anxiety tend to view learning management systems as more difficult to use; however, these effects may be decreased if the students' levels of confidence in their computer skills (i.e. computer self-efficacy) can be improved.

Computer anxiety and computer self-efficacy have also been shown to impact performance. Vician and Davis (2002) collected questionnaire data on 188 students in an undergraduate information systems course. They examined computer anxiety, oral and written communication apprehension, and performance. Computer anxiety was found to be negatively correlated to performance in this computing-intensive environment.

A later study (Buche et al., 2007) involving these authors investigated changes in computer anxiety and performance through exposure to a computing-intensive environment. Sixty-nine introductory information system students completed questionnaires at the beginning and end of the course. The results indicated that the initial level of computer anxiety influenced whether or not a significant change occurred. Those scoring high in computer anxiety initially demonstrated significant changes in computer anxiety but the direction of the change was not significant. This means that some of these students experienced reduced computer anxiety and some experienced increased computer anxiety after the course. Students with high levels of computer anxiety tended to perform worse in the course compared to the low computer anxiety students as measured by final course grade, but an interaction was observed for high computer anxiety and change in computer anxiety. The impact of changes in computer anxiety on performance depended on the initial level of computer anxiety. This interaction was negative in nature. Students who initially had high levels of computer anxiety and who then reported lower levels of computer anxiety at the end of the course tended to perform better. Those students who initially had high levels of computer anxiety and experienced an increase in computer anxiety at the end of the course tended to perform worse. Since these students completed the course and were exposed to the computing-intensive environment, this demonstrates more than just exposure and experience is needed to reduce computer anxiety and improve performance.

This initial level of anxiety was also seen as an important factor in a study by Beaudry and Pinsonneault (2010). This meta-analysis indicated that participants who reported high levels of anxiety distanced themselves more psychologically and used information technology less than those reporting lower levels of anxiety. Additionally, the authors reported that emotions felt early in technology use had lasting effects.

This supports earlier research by Desai (2001). In this two study series students in introductory business computer courses received an intervention between the midterm and final exams that included additional assistance, coaching, and monitoring. Repeated measures of computer anxiety and test anxiety were measured prior to each exam. Results indicated that computer anxiety decreased prior to the final exam but performance decreased from the midterm to the final exam. This provides further support that simply exposing students to a computing-intensive environment does not guarantee that performance will improve. Although a meta-analytical study (Chua, Chen, & Wong, 1999) provided some evidence that computer anxiety is negatively correlated with computer experience; the relationship was inconsistent. The studies described (Desai, 2001; Buche et al., 2007) demonstrate that computer anxiety should not be looked at alone. It is important that it be examined alongside computer self-efficacy and computer experience.

Research by Brosnan (1998) determined that computer anxiety and computer self-efficacy may impact performance in different ways. Computer anxiety, computer self-efficacy, and computer experience were measured in 50 traditional-aged undergraduate students. Performance measures included two novel database tasks. The results also revealed that computer anxiety was linked with the number of correct responses, but computer self-efficacy was associated with how the tasks were confronted. Students with higher computer anxiety made fewer correct responses, but those with higher computer self-efficacy used more resources as measured by the number of look-up tables utilized. When the time to complete tasks was examined it was clear that the use of more look-up tables increased time but it also increased the number of correct responses. Computer anxiety was negatively correlated with computer self-efficacy. This indicated that those with lower levels of computer anxiety tended to have higher levels of computer self-efficacy which was associated with increased time due to the use of more look-up tables and more accurate responses. Since computer anxiety was negatively correlated with question total, meaning those with high anxiety answered fewer questions, the authors suggest that this demonstrates possible cognitive interference with high levels of computer anxiety.

Cognitive interference in computer anxiety has been supported by other research. Smith and Caputi (2001) found that students high in computer anxiety reported more off-task thoughts and negative evaluations and thoughts about computers. If high levels of computer anxiety lead to more off-task thoughts during computer tasks, then regarding online learning environments this may lead to decreased engagement in the courseroom. This decrease in engagement may in turn lead to decreased performance as previously discussed (Hirschfield & Gasper, 2011).

Social cognitive theory would predict that high computer anxiety and low computer self-efficacy may lead online students to avoid or give up easily when faced with challenging tasks. This prediction has been supported in the published literature. Shapka and Ferrari (2003) examined how computer self-efficacy and computer attitudes in teacher candidates impacted behavior on a challenging computer task. They found that candidates for elementary education with lower computer self-efficacy predicted they would avoid or give up on a challenging task more often than their counterparts preparing for secondary education, even though there were no differences found in the actual performance of these groups. Computer experience was also measured and the results showed that the candidates for secondary education who reported higher levels of computer self-efficacy also reported more computer experience.

Computer anxiety has been shown to influence one's perceived behavioral control (Elle-Dit-Cosaque, Pallud, & Kalika, 2011). This research took place in a vocational training program and measured workers' attitudes toward increased implementation of information technology within various industries. In addition to the negative relationship between computer anxiety and perceived behavioral control, results also indicated a positive relationship between perceived behavioral control and innovativeness with information technology, which are similar to computer self-efficacy. This study also underscores the importance of computer experience as certain aspects of the program, including increased autonomy, offering appropriate support, and reducing overload, can reduce computer anxiety and increase perceived behavioral control. This perception of behavioral control may be an important factor to persistence and motivation to complete challenging tasks.

Social cognitive research by Bandura and his associates has shown that goal setting and feedback on performance are important to self-efficacy (Bandura & Cervone, 1983) and that successes and failures can impact reported self-efficacy and future goal setting (Bandura & Locke, 2003). Additionally, it is critical that one believes that improvement is possible. Wood and Bandura (1989) researched simulated organizational performance based upon the decisions of participants in a challenging managerial task. The concept of ability was manipulated, either presented as a static quality that one possesses or as an acquired skill that improves with practice. Those in the static ability condition demonstrated a decrease in self-efficacy, poorer organizational performance, and set easier goals throughout the simulation. Conversely, those in the acquired skill condition showed slightly improved self-efficacy, set challenging goals, were more effective in their use of analytical strategies, and maintained consistent levels of organizational performance. Also, the participants in the static ability condition tended to make more changes in their use of motivational strategies, but not in an optimal way to utilize performance feedback.

Taken together, the reviewed literature discussed emphasizes the importance of computer anxiety, computer self-efficacy, and computer experience in engagement and performance for online students. One's comfort level with computers and perceived ability to perform those tasks are impacted by one's experiences and these factors together may influence how one interacts within the courseroom and ultimately performs in that setting.

Methodology and Analyses

The literature review also included an investigation of how computer anxiety, computer self-efficacy, computer experience, performance, and engagement are methodologically examined. For research to be effective and useful the methodology and analysis must be appropriate for the research problem and answer the research question (Rogers, 1995). Many of the studies in this area of research used quantitative methodology (e.g., Alenezi et al.., 2010; Conrad & Munro, 2008).

Quantitative methodology, as the name implies, assigns numerical values to variables. These research designs adhere to the assumptions of logical positivism, such as the belief in an objective reality and the ability to measure that reality. The use of quantitative data is present in published literature from a variety of countries around the world including, but not limited to, Germany (Hank, 2015), Greece (Palaigeorgiou, Siozos, Konstantakis, & Tsoukalas, 2005), and Saudi Arabia (Alenezi et al., 2010). A myriad of topics has been investigated using quantitative methods including, but not limited to, self-esteem (Hank, 2015), physical activity in patients with multiple sclerosis (Motl, McAuley, & Klaren, 2014), sleep in commercial drivers (Lemke, Apostolopoulos, Hege, Sönmez, & Wideman, 2016), and post-traumatic stress disorder (Daniels, Boehnlein, & McCallion, 2015).

Various avenues of measuring variables are used including, but not limited to, behavioral observations (Kirsch, Rohlf, & Krahé, 2015), self-reports (Turner & Leach, 2010), and reports from significant others (McCrae & Costa, 1987). Kirsch et al. (2015) used a behavioral observation measure to investigate anger regulation in children. Children were observed while completing an anger-eliciting task and reactions were recorded on a behavioral observation form designed for this purpose. Additionally, self-reports were obtained and compared to the observed behaviors. Results indicated that self-reported predictions of future behavior were positively correlated with the observed behaviors at a later time. This supports the validity of using self-reports to collect data.

Self-reported data obtained from surveys and questionnaires are popular within the published literature. Turner and Leach (2010) used self-report data to measure the impact of treatment on anxiety. A repeated measures design was used to collect data on anxiety levels prior to treatment, immediately following treatment, and at a three-month follow-up. The results indicated that treatment was effective in reducing reported anxiety and increased activity levels in the participants.

In addition to self-reports, reports from significant others have been used to collect quantitative data. McCrae and Costa (1987) used both self-reports and significant other-reports to collect personality data and assess the validation of the five-factor model. This study revealed a significant correlation between self- and other-reports providing support not only for usefulness of quantitative methods, but also the use of self-reports as a valid data collection tool.

Just as the methodology must be appropriate for the research problem and research question, the analyses performed must be driven by the research question and the type of data collected (Rogers, 1995). Regression analysis allows predictions on an outcome variable based upon various predictor variables (Warner, 2013). The type of regression analysis conducted depends upon the data type of the predictor and outcome variables. Logistic regression is used for analysis of categorical outcome variables (Finch & Schneider, 2007; Warner, 2013) and demonstrates if outcome group membership can be determined. The acceptance of these analyses by the scientific community is evident in the published literature of a variety of topics. Binary logistic regression has been used to examine person-organization fit (Merecz-kot & Andysz, 2017), adequacy of follow-up treatment for post-traumatic stress disorder (Sripada et al., 2016), and point cloud scanning (Stal et al., 2014). In the current study, binary logistic regression was used to determine if computer anxiety, computer self-efficacy, and computer experience can predict successful versus unsuccessful performance in the online courseroom.

Linear regression is used for analyses involving numerical predictor and outcome variables (Warner, 2013). Multiple linear regression allows an examination of the impact of two or more predictor variables on the outcome variable (George & Mallery, 2014). This type of analysis is prevalent in the published literature and has been used to investigate numerous topics including, but not limited to, software effort estimations in the development of new software

(Fedotova, Teixeira, & Alvelos, 2013), accounting for data errors in an audit (Shepherd & Yu, 2011), decision-making tasks (Buelow & Barnhart, 2017), and mathematical courseware engagement (Spence & Usher, 2007). Multiple linear regression was used in the current research to examine the prediction of engagement in the online courseroom from scores on computer anxiety, computer self-efficacy, and computer experience.

Findings

The previous research has illustrated how computer anxiety, computer self-efficacy, and computer experience are related and how they may influence classroom engagement and performance. The negative association of computer anxiety with performance has been well-documented (e.g., Vician & Davis, 2002) as well as the positive relationship between computer self-efficacy and performance (e.g., Hauser et al., 2012). These studies established that high levels of computer anxiety and low levels of computer self-efficacy could lead to impaired performance in computer-intensive environments. Given the increased popularity of online education (Allen et al., 2016), these factors may be barriers to successful completion of educational goals for some students.

Furthermore, the research on engagement indicates that students who are less engaged in the classroom tend to perform poorer compared with those who are more engaged (Fall & Roberts, 2012). The effect of computer self-efficacy in online courseroom engagement has been documented (Spence & Usher, 2007) and cannot be ignored. One's computer self-efficacy can impact how challenging tasks are approached and how persistent one will be to complete those tasks.

Critique of Previous Research Methods

The variables of interest in this study have been researched extensively over the past two decades. Since these variables are measuring characteristics already present in the participants, they have been examined using non-experimental methods, mostly correlational designs (e.g. Deryakulu & Caliskan, 2012). A few studies went a step further and looked at the predictive nature of these variables on performance using regression analysis (e.g. Arning & Ziefle, 2008; Vician & Davis, 2002). However, due to the lack of experimental control in this body of research any inferences and generalizations must be made cautiously. Repeated measures designs (Wild et al., 2012b) have been used but these also lacked random assignment so the changes in computer anxiety and computer self-efficacy must be interpreted carefully. The impact of cognitive-affective states, including anxiety but not computer anxiety, have been studied experimentally in a computer-intensive environment by Wang, Ryu, and Katuk (2015). Even though this research indicated that cognitive-affective states impacted performance, it did not specifically examine computer anxiety. The research reviewed here indicated that a complex relationship exists among these variables but the scarcity of experimental research designs in this body of literature stresses that inferences of causation cannot be made.

Various combinations of these variables have been studied but mostly within the context of specific computer tasks. For example, achievement in an introductory statistics course requiring the use of a specific statistic program (Abd-El-Fattah, 2005), a database task (Brosnan, 1998), learning information systems foundations, and a business programming language (Buche et al., 2007) have been the focus of investigation. Engagement with mathematics software has been examined (Spence & Usher, 2007), but this was also within the parameters of a specific computer task. There is little evidence of how these variables would interact with performance and engagement in an online course where the computer tasks were supportive to the graded assignments in a general education course which is the focus of the current research project.

There have been several studies on computer anxiety, computer self-efficacy, and computer experience, but in many of the studies not all the variables were included (e.g. Smith & Caputi, 2001). For instance, many of the studies with college students focused on traditional face-to-face courses, such as Wilfong (2006) and Fuller, Vician, and Brown (2006). Some of the studies used online students as participants (e.g., Hauser et al., 2012; Saadé & Kira, 2009); however, they did not include all the variables. The current research focuses on all the variables and their ability to predict performance and engagement in an online course for community college students.

Engagement has been investigated in elementary and middle school age children (Hirschfield & Gasper, 2011) and high school students (Bilge et al., 2014), but these studies did not address the current population of interest – online community college students. Prediction of engagement in college age students from personal characteristics has been investigated (Keller & Karau, 2013b). Engagement in college students has also been examined in relation to computer-based assessment, satisfaction and pass rates (Nguyen, Rienties, Toetenel, Ferguson, & Whitelock, 2017). However, the previous studies failed to address the current research question regarding the prediction of engagement in community college students from computer anxiety, computer self-efficacy, and computer experience.

The current study fills a gap in the extant literature by including all of the variables of interest in a single study. Additionally, examining whether performance and engagement in a college age population can be predicted by computer anxiety, computer self-efficacy, and computer experience is a unique approach.

Summary

The current research fills a gap in the literature by examining the ability of computer anxiety, computer self-efficacy, and computer experience to predict levels of engagement and successful performance in general education online students. Evidence has been presented that computer anxiety negatively impacts performance (e.g. Abd-El-Fattah, 2005) and that computer self-efficacy explains just under half of the variance in performance (Brosnan, 1998). Empirical evidence has also shown that engagement and performance on computer tasks in computer-intensive environments are impacted by computer anxiety and computer self-efficacy. However, there is no evidence to date on how performance in general education courses, where the computer skills are not content-related, could be influenced by these variables.

CHAPTER 3. METHODOLOGY

This chapter will review the specific methodology and research design utilized for this study. It is important for replication and critical evaluation that procedures employed are clearly outlined. The purpose, research questions, and hypotheses will be explained in detail. The procedures including target population, participant selection, and instruments administered will be presented. Finally, data analyses and ethical considerations will be described.

Purpose of the Study

Extant literature has shown that online learning continues to rise in popularity (Allen et al., 2016; Greenland & Moore, 2014). Alleviation of barriers to success for these students is critical to retention and degree completion. One barrier to success may be student comfort level with computers and its impact on performance and engagement.

The purpose of this study was to identify levels of computer anxiety, computer self-efficacy, and computer experience in online community college students and to determine whether or not these variables predict performance and engagement in an online general education course. The results of this study could add to the body of knowledge regarding barriers to success in online education and could be used by colleges and universities to increase student success. For instance, Fagan et al.'s (2003) research found that students scoring higher in computer anxiety spent more time in the computer lab, which may indicate that more time may be required for students scoring higher in computer anxiety to complete assignments that include computer tasks.

Research Questions and Hypotheses

Research Question #1

Do scores on measures of computer anxiety, computer self-efficacy, and computer experience predict successful course completion of a general education course in online community college students?

H_0 – Scores on measures of computer anxiety, computer self-efficacy, and computer experience do not predict successful course completion of a general education course in online community college students.

H_1 - Scores on measures of computer anxiety, computer self-efficacy, and computer experience predict successful course completion of a general education course in online community college students.

Subquestions

- Do males and females differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict successful course completion of a general education course in online community college students?

H_0 - Males and females do not differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict successful course completion of a general education course in online community college students.

H_1 - Males and females differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict successful course completion of a general education course in online community college students.

- Do participants from different majors differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict successful course completion of a general education course in online community college students?

H_0 - Participants from different majors do not differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict successful course completion of a general education course in online community college students.

H_1 - Participants from different majors differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict successful course completion of a general education course in online community college students.

Research Question #2

Do scores on measures of computer anxiety, computer self-efficacy, and computer experience predict course engagement in a general education course in online community college students?

H_0 – Scores on measures of computer anxiety, computer self-efficacy, and computer experience do not predict course engagement in a general education course in online community college students.

H_1 - Scores on measures of computer anxiety, computer self-efficacy, and computer experience predict course engagement in a general education course in online community college students.

Subquestions

- Do males and females differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict engagement in a general education course in online community college students?

H_0 - Males and females do not differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict course engagement in a general education course in online community college students.

H_1 - Males and females differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict course engagement in a general education course in online community college students.

- Do participants from different majors differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict course engagement in a general education course in online community college students?

H_0 - Participants from different majors do not differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict course engagement in a general education course in online community college students.

H_1 - Participants from different majors differ in the ability of scores on measures of computer anxiety, computer self-efficacy, and computer experience to predict course engagement in a general education course in online community college students.

Research Design

A non-experimental, non-randomized research design was used to answer these research questions. Non-experimental designs are used when the strict requirements for experimental designs, such as random selection and random assignment, cannot be used (Warner, 2013). Non-experimental research designs allow correlational relationships to be revealed; however, a limitation of non-experimental designs is that causation cannot be inferred (Warner, 2013). Although non-experimental designs have limitations, they are widely used and accepted as a legitimate research design (e.g. Vazire & Mehl, 2008). Non-experimental designs have been used to examine a variety of topics including stress and satisfaction (Fuller et al., 2003), child development (Harkness, 1992), and sleep quality in commercial truck drivers (Lemke et al., 2016).

This study was considered non-experimental because the volunteers were self-selected through enrollment in an online general education course at the community college and their participation was voluntary. Therefore, no random selection or random assignment existed. Additionally, all participants completed the same surveys and there were no varying treatment conditions as in experimental designs (Warner, 2013).

Target Population and Sample

Population

The population of interest was students enrolled in online general education courses at a community college. The student body of a community college consists of a wide variety of ages, ethnicities, academic abilities, and external responsibilities (Liu et al., 2007). According to the American Association of Community Colleges (2016), nearly half (45%) of all undergraduates in the United States were enrolled in community colleges including 41% of first-time freshman. Many of the students attended school part-time and most were employed. The average age of community colleges students was 28, with nearly half being in the 22-39 age group (49%). Women made up 57% of the community college population.

Sample

Participants were those available to the researcher through the community college which made this a non-probability, convenience sample (Leedy & Ormrod, 2013). Convenience samples come with limitations in the transferability of the results (Leedy & Ormond, 2013); however, have often been used in published research on a variety of topics, such as Post-

Traumatic Stress Disorder in veterans (Daniels et al., 2015), attitudes toward distance learning (Hashim, Ahmad, & Abdullah, 2010) and behavioral reports of daily behavior (Vazire & Mehl, 2008).

All students enrolled in an online general education course at the community college were invited to participate. Inclusion criteria included enrollment in an online general education course at the community college and being over the age of 18 years. Students who were under the age of 18 were excluded.

Power Analysis

A power analysis was conducted using G*power (Faul, Erdfelder, Lang, & Buchner, 2007). Analyses for both research questions were based upon power set at .80, an .05 alpha level, and with a medium effect size, as recommended by Warner (2013) and Cohen (2016). The risk of committing a Type I error (rejecting a true null hypothesis), was controlled by using an alpha level of .05. The risk of committing a Type II error (accepting a false null hypothesis) was moderated by the .80 level of power. A sample size of 77 was recommended for both research questions based upon this analysis.

Procedures

Participant Selection

Recruitment Site. Volunteers were recruited from a large rural community college in the central United States. Permission was obtained from the Human Subjects Review Board at the institution in accordance with the ethical standards of the American Psychological Association (APA; 2010). Although not a part of the formal process, meetings with the Dean of Online Learning and Office for Institutional Effectiveness were held prior to implementation to provide notification and seek recommendations for the project. Additionally, approval was received from Capella University's Institutional Review Board prior to recruitment or data collection.

Recruitment. Online general education faculty were sent an email request to post the invitation to participate in their online courserooms. The email included the invitation to participate and instructions to post it verbatim. The institution sent a notice in advance that this email would be sent so the faculty would know this was an approved research project. It is unknown which faculty posted the invitation and the researcher did not have access to the courserooms. This minimized the risk of coercion since the researcher was a colleague to these faculty. Volunteers received the invitation to participate in their courseroom and those interested were directed to a Qualtrics link. APA ethical guidelines (2010) require researchers to protect volunteers' identifiable information. The use of Qualtrics protected the identities of the participants. Informed consent was obtained prior to any data collection.

Contact with Researcher. Volunteers must be given adequate information for them to consent to participate (APA, 2010). Therefore, volunteers received contact information for the researcher and dissertation mentor when directed to Qualtrics so any questions regarding the research could be answered. The information provided included the telephone number and email address for the researcher and the email address for the dissertation mentor. Volunteers may use this information to contact the researcher and/or dissertation mentor at any time during the research process. The identity of any volunteers who contact the researcher and/or dissertation mentor will be secured to protect personally identifiable information. The researcher had no direct contact with the participants unless initiated by the participant. No participants have contacted the researcher.

Participant Screening. The invitation to participate included the inclusion and exclusion criteria. Additionally, the informed consent reiterated these criteria. By giving consent to participate, the volunteers confirmed that all participants met the inclusion criteria and did not meet the exclusion criteria. When consent to participate was given, the participant was presented with the survey questions. Participants could discontinue at any time or skip any questions without penalty. If a volunteer indicated that he/she did not meet the inclusion criteria, or chose not to participate, the volunteer was directed to a thank you message. Coercion to participate is prohibited by APA ethical guidelines (2010); therefore, participants could discontinue their participation without penalty.

Protection of Participants

Guidelines set forth by the APA (2010) were followed to ensure that participants were protected from harm. Participation was voluntary so that no coercion occurred. Informed consent was obtained prior to any data collection. Additionally, the use of Qualtrics for data collection ensured anonymity. No data was collected that could identify participants nor the device through which they completed the survey. The researcher received a report containing the raw data collected.

Data Collection

After receiving the invitation to participate through the online courseroom, participants were directed to Qualtrics to access the survey which could be completed from any computer. Only those receiving an invitation to participate could access the survey.

The first item presented was the informed consent which explained the procedures and rights of the participants. The remainder of the survey consisted of five sections that corresponded to the constructs and incorporated three published instruments and two instruments created for this project. Part A was a demographic and performance survey designed for this project. Part B was the Computer Anxiety Scale (Wild et al., 2012a), Part C was a Computer Experience survey designed for this project, Part D was the Computer Self-Efficacy Scale (Compeau & Higgins, 1995), and Part E was the Online Course Impressions Instrument (Keller & Karau, 2013a) which measures engagement. Qualtrics estimated that the survey would take participants approximately 30 minutes to complete.

The target number of surveys was 90 based on the 77 recommended by G*power (Faul et al., 2007), plus 15% to allow for invalid cases. The number of completed surveys was monitored every two to three days and when the target number of completed surveys was collected, the survey was closed. All data were downloaded to a password protected computer file. After analysis was complete, the data were stored on a memory stick and kept in a locked filing cabinet to which only the researcher has access. After the mandatory period of seven years it will be destroyed.

Data Analysis

Qualtrics provided data in a format compatible with Statistical Package for the Social Sciences version 24 (SPSS). The data was examined for accuracy and manipulated to prepare it for analysis. This section details chronologically how the data were treated.

The raw data were imported into SPSS from Qualtrics. The data set was examined to ensure that variables were arranged in a manner that would facilitate easy management. The data set was examined using SPSS Case Summaries to identify missing variables, incomplete cases, and improperly coded data (George & Mallery, 2014). These cases were omitted from the analysis so as not to skew the data (George & Mallery, 2014). The first three cases were deleted from the data set as these were test cases and not responses from participants.

Course performance and engagement were the outcome variables and were measured using a categorical scale and an interval scale, respectively. Predictor variables computer anxiety, computer self-efficacy, and computer experience were measured on quantitative interval scales and the predictor variables of gender and academic major were measured on nominal scales.

The SPSS Recode command was used to change reverse scored items into the proper format so that the meaning of these answers was consistent with the other items. The computer anxiety and engagement sections of the survey contained the reversed items. The recoded items were then included in the scale scores. Computer experience questions, which were phrased as string variables, were changed into a numeric scale. The Compute command was used to calculate aggregate scores for computer anxiety, computer self-efficacy, engagement, and total computer experience. Academic major was recoded to group similar majors together. The following academic major categories were created: Business, Education, Medical, Science, Social Science, Technical/Engineering, and Other. The SPSS Recode command (George & Mallery, 2014) was also used to categorize the outcome variable course performance into Successful and Unsuccessful. For performance, the category of C or above was coded as successful and the categories of D or below and Withdrew/Dropped were combined and coded as unsuccessful completion. The SPSS Create Dummy Code command was used to recode the predictor variables gender and academic major. Since they are categorical variables, this was necessary to include them in a multiple linear regression analysis. Gender was recoded as male (G_1), and the reference group is female. The academic major variable was recoded as Business (M_1), Education (M_2), Medical (M_3), Science (M_4), Social Science (M_5), Technical/Engineering (M_6), and the reference group is Other.

Descriptive statistics were analyzed for all key variables to describe the sample, examine the integrity of the data, and confirm that the assumptions of the analyses were met. The assumptions for binary logistic regression are as follows: a dichotomous outcome variable, independence of scores, inclusion of all relevant predictors, and outcome variable levels that are exhaustive and mutually exclusive (Warner, 2013). The assumptions for multiple linear regression are as follows: a quantitative outcome variable, linearity among all pairs of variables, homogeneous regressions, and similar variance within the variables (Warner, 2013). These assumptions were evaluated prior to hypothesis testing.

Research question #1 and its subquestions were evaluated using a binary logistic regression. The predictor variables were computer anxiety, computer self-efficacy, and computer experience, and the outcome variable was course performance. This is the appropriate procedure to predict a categorical outcome variable (Finch & Schneider, 2007; Warner, 2013; Wintre & Bowers, 2007). Research question #2 and its subquestions were evaluated using a multiple linear regression with stepwise backward elimination. The predictor variables were computer anxiety, computer self-efficacy, and computer experience, and the outcome variable was engagement. This is the appropriate procedure to predict a numerical outcome score on an interval scale (Warner, 2013). The research questions were analyzed using stepwise backward elimination which includes all of the predictor variables in the model and then predictor variables are removed from the model beginning with the least predictive (George & Mallery, 2014). This type of elimination of variables results in a final model that includes the most predictive variables.

Post hoc analyses were performed to more fully explore the results of hypothesis testing. Post hoc analyses included *t*-test and Analysis of Variance (ANOVA) procedures. These analyses may assist with interpretations of the results. A research log was maintained to record any key issues and decisions regarding the data.

Instruments

Computer Anxiety Scale

Computer anxiety was measured using the Computer Anxiety Scale (Wild et al., 2012a) which uses a five-point Likert scale to indicate agreement with 16 items. The Computer Anxiety Scale provides a single score with higher scores indicating higher levels of computer anxiety. The survey was published by the American Psychological Association in PsycTESTS and is available for use.

Reliability. During the design phase, the Computer Anxiety Scale (Wild et al., 2012a) demonstrated test-retest reliability ($r = .68$, $p < .0001$) at a one-year follow-up (Wild et al., 2012b). This means that when their participants were retested one year later approximately 46 % of the variance in scores could be predicted by the initial scores. This is considered a modest reliability estimate and it is in an acceptable range (Warner, 2013).

Validity. The Computer Anxiety Survey (Wild et al., 2012a) was developed using a principal component analysis with varimax rotation which revealed three factors: Anxiety/Tension, Confidence/Contentment, and Computer Use, having eigenvalues of 8.6, 1.3, and 0.9, respectively (Wild et al., 2012b). Each item loaded significantly on only one factor indicating that each measured a different construct. Although three factors were identified, the survey is scored to produce a single score.

Computer Self-Efficacy Scale

Computer self-efficacy was measured using the Computer Self-Efficacy Scale (Compeau & Higgins, 1995) which has 10 items and uses a 10-point Likert scale to indicate confidence in completing specific computer tasks. Participants received a single score, with higher scores indicating higher levels of computer self-efficacy. The survey was published in a public journal and is available for use; however, the first author was contacted by email and she affirmed that her permission was not necessary.

Reliability. The Computer Self-Efficacy Scale was found to have high internal consistency (r > .80; Compeau & Higgins, 1995). Later studies also revealed high internal consistency reliability scores of .94 (Compeau, Higgins, & Huff, 1999) and .95 (Shu, Tu, & Wang, 2011).

Validity. The development of The Computer Self-Efficacy Scale included an examination of its discriminant validity and construct validity. Discriminant validity (Compeau & Higgins, 1995) was demonstrated since these items were distinct from items which loaded on other factors identified in the model, such as encouragement, other's use, support, outcome expectations, affect, anxiety, and use. Construct validity was demonstrated by its positive relationship with expected constructs, such as high-performance outcome expectations, and negative relationships with expected constructs, such as anxiety (Compeau & Higgins, 1995).

Online Course Impressions Instrument

Engagement in the online course was measured using the Online Course Impressions Instrument (Keller & Karau, 2013a) which was published by the American Psychological Association in PsycTESTS and is available for use. It includes 26 items using a five-point Likert scale and provides scores on five scales: engagement, value to career, overall evaluation, anxiety/frustration, and preference for online courses. However, only the Engagement subscale was analyzed. The Engagement scale includes six items scored on a five-point Likert scale. Each participant received a score between 6 and 30 for engagement with higher scores indicating higher levels of engagement. This survey was developed using a sample of 250 online college students which included a variety of academic majors, marital and family statuses, and ages.

Reliability. The Online Course Impressions Survey has demonstrated adequate internal consistency (engagement scale, $a = .86$) indicating that items on the scale are highly correlated (Keller & Karau, 2013b).

Validity. The Engagement subscale demonstrated construct validity (Keller & Karau, 2013b) by correlating with the expected scales of the Big Five personality factors (McCrae & Costa, 1987), Agreeableness ($r = .17$, $p < .01$), Conscientiousness ($r = .39$, $p < .01$), and Openness ($r = .18$, $p < .01$).

Computer Experience Survey

Computer experience was measured using an instrument designed for this research project. The survey contains three items about years of computer use, number of previous online courses, and number of computer courses. The scores for these items were combined to provide a score for total computer experience.

The investigation of computer experience and ability is complicated by the rapid changes in technology (Kay, 2006). This was evident in research by Bozionelos (2001a) which used different versions of a computer experience scale due to differing collection times. This alteration of the scale was performed at the recommendation of information technology specialists (Bozionelos, 2001a). R. Kay (personal communication, January 28, 2016) advised that his scales (Kay, 1993; Kay, 2006) were outdated and recommended updating them prior to their use. Many published research articles on computer experience used items designed for the specific topic of interest (Abd-El-Fattah, 2005; Arning & Ziefle, 2008; Birgin, Çatlıoğlu, Gürbüz, & Aydın, 2010; Havelka et al., 2004; Miller, Stanney, & Wooten, 1997). The number of items ranged from a single item (Abd-El-Fattah, 2005) to seven items (Birgin et al., 2010). This practice of focusing on a specific type of computer experience supports Kay's (2006) recommendation that computer skills relevant to the context of interest be examined. Following this precedent, a survey was designed to focus on the contextually important skills to an online educational environment. This survey contained questions about years of computer use, the number of online courses completed, and number of computer courses completed.

Demographic Survey

A survey to collect demographic and performance information was designed for this specific research project. The demographic portion collected information regarding age, gender, academic major, and degree pursued. A self-report performance survey was used to collect data on final course grade.

Ethical Considerations

The Belmont Report (1979) and the American Psychological Association (APA; 2010) established guidelines to ensure the ethical treatment of participants. The principle of Justice and Nonmaleficence is designed to ensure that all people have access to and opportunity to benefit from research findings (APA, 2010). This research violates this principle in that all community college students did not have an opportunity to participate; however, the results will be shared, as appropriate, to the psychological community. The principle of Beneficence requires that participants be protected from harm (APA, 2010). This research had minimal risk that did not exceed risk from participation in daily activities. The research did not focus on a vulnerable population. The principle of Respect for People's Rights and Dignity (APA, 2010) necessitates that participants' rights to autonomy be protected and that they be treated with dignity. Informed consent was obtained from each participant and the procedures were free of coercion. Data collection was performed through Qualtrics to protect the identity of the participants; therefore, participation was anonymous. The sample included only the number of participants recommended to achieve acceptable statistical power so that participants' time was respected. The Human Subjects Review Board for the community college and the Institutional Review Board of Capella University approved the research prior to recruitment and data collection.

Summary

The purpose of this study was to investigate computer anxiety, computer self-efficacy, computer experience in community college students and the ability of these variables to predict engagement and successful course completion of online general education courses. This non-experimental design used non-randomized convenience sampling and an online survey format. The data were analyzed using binary logistic regression and multilinear regression analyses. The results of these analyses are presented in Chapter 4.

CHAPTER 4. RESULTS

Background

The purpose of this research was to examine the predictive ability of computer anxiety, computer self-efficacy, and computer experience regarding engagement and performance in online general education courses. The theoretical foundations and previous research has been presented in Chapters 1 and 2 along with a description of methodology and design in Chapter 3. This chapter will describe the sample, descriptive statistics of the data collected, statistical analyses performed to test the hypotheses, and the results of those analyses.

Description of the Sample

All students enrolled in an online general education course at the community college were invited to participate. One hundred thirteen volunteers responded to the invitation. The average time participants took to complete the survey was 13 minutes.

Five did not agree to the informed consent and were not presented with the survey, leaving 108 participants who answered the survey. The sample included 19 males (16.8 %) and 87 females (77%) with 7 participants not providing this information (see Table 1).

Table 1
Characteristics of Sample

Characteristic	Frequency	Percent
Gender		
Male	19	16.80
Female	87	77
Unknown	7	6.20
Academic Major		
Business	13	11.50
Education	8	7.10
Medical	36	31.90
Science	7	6.20
Social Science	18	15.9
Technical/Engineering	14	12.40
Other	9	8

The academic majors of the sample are also listed in Table 1. Over 30% (n = 36) of the participants were pursuing a degree in the health care field and nearly 16% (n = 18) were studying the social sciences. Eight (7.1%) participants did not provide their academic major.

Due to the community college offering academic and technical programs, data were also collected regarding type of degree participants were pursuing. The following academic degrees were identified by participants: Associates of Arts (23.6%), Associates of Science (38.9%), and Associates of Applied Science (29.2%). The following technical programs were identified by participants: Technical Certificate (4.2%) and Technical Degree (4.2%).

Descriptive Statistics

Descriptive statistics for the continuous quantitative variables are summarized in Table 2. Computer anxiety scores ranged from 16.00 to 59.00 with a mean of 32.93 (SD = 12.09). The skewness and kurtosis values for computer anxiety were in the excellent range, .34 and -.89 respectively, indicating that the distribution of scores within the sample did not significantly differ from a normal distribution. However, the Shapiro-Wilk test of normality was significant indicating that the sample deviated from a normal distribution, $W = .92$, p = .01. Computer self-efficacy scores ranged from 52.00 to 100.00 with a mean of 83.64 ($SD = 13.56$). The skewness and kurtosis values for computer self-efficacy were also in the excellent range, -.50 and -.60 respectively. The Shapiro-Wilk result was significant, $W = .93$, p = .03. Engagement scores ranged from 10.00 to 27.00 with a mean of 20.18 ($SD = 3.65$). The skewness value for engagement was -.16 and kurtosis value was -.32, both of which were in the excellent range. The Shapiro-Wilk value, $W = .95$, $p = .15$, supported that the distribution of scores did not deviate significantly from a normal distribution. Scores for predictor variables, computer anxiety and computer self-efficacy were classified as low, moderate, and high to better understand the sample. Sixty-eight percent of the sample endorsed low levels of computer anxiety, 30.6% endorsed moderate levels of computer anxiety, and 1.4% endorsed high levels of computer anxiety. For computer self-efficacy, no participants reported low levels, 9.7% reported moderate levels, and 44.4% reported high levels. Approximately 45% of the participants did not complete all computer self-efficacy items. These cases were not included in computer self-efficacy analyses. Potential limitations of these omissions will be discussed in Chapter 5.

Years of computer experience scores ranged from 1.00 to 35.00 with a mean of 15.58 ($SD = 7.64$). The skewness and kurtosis values for years of computer experience were in the excellent range, .89 and .33 respectively. Conversely, the Shapiro-Wilk value was significant, W = .92, $p = .01$, indicating that normality of distribution was violated. Number of online courses completed (CE_online) ranged from 0.00 to 30.00 with a mean of 6.12 ($SD = 6.26$). The skewness value for number of online courses completed was 1.44 and the kurtosis value was 1.74, which were in the acceptable range. The Shapiro-Wilk value, W = .87, $p = .00$, for number of online courses completed indicated that the sample was not normally distributed. Number of computer courses completed (CE_com) ranged from 0.00 to 40.00 with a mean of 5.97 (*SD* = 7.42). The skewness value for number of computer courses completed was 1.95 which is in the acceptable range. The kurtosis value (4.52) for number of computer courses completed was not in the acceptable range nor was the Shapiro-Wilk value, W = .70, $p = .00$. The kurtosis value indicated that this sample is leptokurtic, which means the scores peak sharply in the center and there are fewer scores at the ends of the distribution. These computer experience scores were summed to create a total score with a range of 5.00 to 73.00 with a mean of 28.09 (*SD* = 14.21). The skewness and kurtosis values for total computer experience were .89 and .81 respectively, which were in the excellent range. The Shapiro-Wilk value for total computer experience was significant, W = .94, $p = .04$, which means that the distribution of scores in this sample deviated from normality.

Table 2
Descriptive Statistics of Predictor and Outcome Variables

					Shapiro-Wilk	
	N	M (SD)	Skewness	Kurtosis	Statistic	*p*
Computer Anxiety	93	33.19 (11.95)	.34	-.89	.92	.01
Computer Self-Efficacy	45	83.44 (12.97)	-.50	-.60	.93	.03
Engagement	89	19.92 (3.68)	-.16	-.32	.95	.15
Yrs of Computer Experience	92	15.58 (7.64)	.89	.33	.92	.01
Number of Online Courses	91	6.12 (6.26)	1.44	1.74	.87	.00
Number of Computer Courses	87	5.97 (7.43)	1.95	4.52	.70	.00
Total Computer Experience	86	28.09 (14.21)	.89	.81	.94	.04

The frequencies for the categorical predictive variables of gender and academic major are presented in Table 1. The frequencies for the categorical outcome variable of performance is presented in Table 3 below. The results show that 90% (n = 65) of the participants reported successfully completing an online general education course with a C or above.

Table 3
Performance of Participants

Performance	Frequency	Percent
Successful	65	90.30
Unsuccessful	7	9.7

Assumptions of Binary Logistic Regression and Linear Regression

As stated previously, the use of binary logistic regression assumes that the data includes a dichotomous outcome variable, independence of scores, inclusion of all relevant predictors, and outcome variables are exhaustive and mutually exclusive (Warner, 2013). This data set meets these criteria for the analysis of research question #1 using performance as an outcome variable. Additionally, it is recommended that all cells have at least five cases and predictor variables not include extreme outliers (Warner 2013). Tables 1, 2, and 3 demonstrate that all cells include more than five cases without extreme outliers.

The assumptions of multiple linear regression require a quantitative outcome variable, normal distribution, linearity among variables, and homogenous variance (Warner, 2013). This data set meets most of the assumptions to perform this analysis. The assessment of normality provided conflicting results. The skewness and kurtosis values are reported in Table 2 which indicated that the data did not deviate significantly from a normal distribution. However, the Shapiro-Wilks results, also reported in Table 2, indicated that normality was violated. This is addressed as a limitation in Chapter 5. The linearity among the variables was evaluated using a correlation matrix which is displayed in Table 4. Computer anxiety was significantly correlated with engagement (r = -.36, p < .01) and computer experience (r = -.32, p < .01). Engagement was also significantly associated with computer experience (r = -.41, p < .01). This demonstrates that these variables are linearly related but not so highly correlated to present multicollinearity issues with the data set.

Table 4
Correlations of Computer Anxiety, Computer Self-efficacy, Engagement, and Computer Experience Total

	Computer Anxiety	Computer Self-efficacy	Engagement	Total Computer Experience
Computer Anxiety	1.00	.10	-.36**	-.32**
Computer Self-Efficacy	.10	1.00	.18	.08
Engagement	-.36**	.19	1.00	.41**
Total Computer Experience	-3.2**	.08	.41**	1.00

**p , .01 (two-tailed).

Hypothesis Testing

Binary logistic regression analyses were performed to answer research question #1 and its subquestions. The over-all model for research question #1 was non-significant, $\chi^2(df = 5) = 4.63$, $p = .463$ (see Table 5), which means that computer anxiety, computer self-efficacy, and computer experience did not predict performance in an online course. The null hypothesis for the subquestion of whether gender improves the ability of the model to predict success was retained, $\chi^2(df = 7) = 5.27$, $p = .627$, which indicates that gender did not significantly contribute to the model. The null hypothesis for the subquestion regarding the ability of academic major to improve the model predictions was also retained, $\chi^2(df = 12) = 20.99$, $p = .051$. This means that a participant's major does not increase the ability of the model to predict successful performance in an online course.

Table 5
Stepwise Backward Binary Logistic Regression Analysis Predicting Performance from Computer Anxiety, Computer Self-efficacy, and Computer Experience

Model	Variables	*B*	*SE B*	X^2	*p*
1				4.63	.46
	Computer Anxiety	.08	.09	.83	.36
	Computer Self-Efficacy	-.11	.09	1.68	.20
	Yrs of Computer Experience	.145	.09	2.45	.12
	Number of Online Courses	.01	.15	.00	.96
	Number of Computer courses	-.01	.13	.01	.92
2				4.63	.32
	Computer Anxiety	.08	.08	.99	.32
	Computer Self-Efficacy	-.11	.07	2.24	.13
	Yrs of Computer Experience	.15	.10	2.45	.12
	Number of Computer courses	-.01	.10	.01	.92
3				4.62	.20
	Computer Anxiety	.08	.08	.99	.32
	Computer Self-Efficacy	-.11	.07	2.20	.14
	Yrs of Computer Experience	.15	.09	2.47	.12
4				3.55	.17
	Computer Self-Efficacy	-.08	.05	2.10	.15
	Yrs of Computer Experience	.12	.09	1.99	.16
5				1.41	.24
	Computer Self-Efficacy	-.05	.05	1.34	.25

Although there were several participants who did not complete all items for the computer self-efficacy survey and were excluded from these analyses, adequate power was demonstrated by the data set. There were 45 cases included in these analyses, which exceeded the recommendation that the number of participants in the sample be at least three times greater than the number of predictor variables in a binary logistic regression (Warner, 2013). Additionally, a post hoc power analysis was performed using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) which indicated 30 cases were required. This provided further evidence that confidence can be had in these results.

Multiple linear regression analyses were performed to answer research question #2 and its subquestions. The overall multiple regression to predict engagement from computer anxiety, computer self-efficacy, years of computer experience, number of online courses completed, and total computer experience predicted 29% of the variance in engagement scores, R = .54 and R^2 = .29, as shown in Table 6. The adjusted R^2 = .19.

The overall regression was statistically significant, $F(5, 34) = 2.79$, p =.03, as shown in Table 6. Therefore, the null hypothesis for research question #2 was rejected and the alternate hypothesis was accepted which means that the overall model including computer anxiety, computer self-efficacy, years of computer experience, number of online courses completed, and total computer experience significantly predicted engagement in an online course. This indicates that a participant's engagement can be predicted if their scores on these variables are known. Complete results for the analysis are shown in Table 6. At each step the least predictive variable in the model is removed. The final regression model retained the most predictive variables, computer anxiety and total computer experience, $F(2, 37) = 6.23$, p =.005. This model predicted 25% of the variance in engagement scores.

Table 6

Stepwise Backward Multiple Regression Analysis Predicting Engagement from Computer Anxiety, Computer Self-efficacy, and Computer Experience

Model	Variables	b	β	*t*	*p*	*R*	R^2	*F*
1	Computer Anxiety	-.14	-.44	-2.89	.007	.54	.29	2.79*
	Computer Self-Efficacy	.05	.21	1.32	.20			
	Yrs of Computer Experience	-.05	-.11	-.51	.62			
	Number of Online Courses	-.09	-.18	-.67	.51			
	Total Computer Experience	.11	.48	1.51	.14			
2	Computer Anxiety	-.13	-.42	-2.89	.007	.53	.29	3.50*
	Computer Self-Efficacy	.05	.18	1.23	.23			
	Number of Online Courses	-.05	-.11	-.47	.64			
	Total Computer Experience	.09	.37	1.66	.11			
3	Computer Anxiety	-.13	-.41	-2.89	.007	.53	.28	4.69**
	Computer Self-Efficacy	.04	.17	1.21	.24			
	Total Computer Experience	.07	.29	2.03	.05			
4	Computer Anxiety	-.12	-.40	-2.78	.009	.50	.25	6.23**
	Total Computer Experience	.07	.29	2.02	.05			

Note.
*p < .05, **p <.01

Since there were a reduced number of cases due to missing computer self-efficacy data the impact of these missing cases on statistical power must be addressed. Decreased power increases the risk of making a Type II error (Warner, 2013), which is failing to reject a false null hypothesis. This analysis resulted in a rejection of the null hypothesis, therefore power is not a critical issue.

Computer anxiety was significantly predictive of engagement when the other variables in the model were statistically controlled, $t(34) = -2.89$, $p = .007$, see Table 6. None of the other variables, computer self-efficacy, years of computer experience, number of online courses completed, nor total computer experience, were significantly predictive of engagement.

When gender was included in the regression model, R = .62 and R^2 = .38 (see Table 7). This means 38% of the variance in engagement scores can be predicted with this model. The adjusted R^2 = .25.

Table 7
Multiple Linear Regression Analysis Predicting Engagement from Computer Anxiety, Computer Self-efficacy, Computer Experience, and Gender

Model	R	R^2	Adjusted R^2
1	.62	.38	.25
Gender, CE_Number of Computer Courses, Yrs of Computer Experience, Computer Self-Efficacy, Computer Anxiety, Number of Online Courses			
2	.61	.38	.27
Gender, Number of Computer Courses, Yrs of Computer Experience, Computer Self-Efficacy, Computer Anxiety			
3	.60	.36	.27
Gender, Number of Computer Courses, Computer Self-Efficacy, Computer Anxiety			
4	.58	.33	.27
Number of Computer Courses, Computer Self-Efficacy, Computer Anxiety			

This means that gender improves the ability of computer anxiety, computer self-efficacy, number of online courses completed, number of computer courses completed, and total computer experience to predict engagement by 9%. The regression model remains a significant predictor of engagement with the inclusion of gender, $F(6, 29) = 2.97$, $p = .02$.

When academic major was included in the regression model, R = .72 and R^2 = .52 (see Table 8). This means that 52% of the variance in engagement scores can be predicted by this model. These results indicate that academic major improves the ability of computer anxiety, computer self-efficacy, number of online courses completed, number of computer courses completed, and total computer experience to predict engagement by 23%. With the addition of academic major added to the model, engagement is still significantly predicted, $F(11,24) = 2.32$, $p = .04$.

Post hoc analyses were performed to determine if engagement scores of participants differed by gender or academic major. A t-test indicated that males and females did not differ in engagement scores. An ANOVA revealed that participants' engagement scores did not differ based on academic major.

Table 8

Multiple Linear Regression Analysis Predicting Engagement from Computer Anxiety, Computer Self-efficacy, Computer Experience, and Academic Major

Model	R	R^2	Adjusted R^2
1	.72	.52	.29
Other Major, Computer Self-Efficacy, Number of Online Courses, Technical/Engineering, Business, Education, Science, Number of Computer Courses, Yrs of Computer Experience, CA, SocSci			
2	.72	.52	.32
Computer Self-Efficacy, Number of Online Courses, Technical/Engineering, Business, Education, Science, Number of Computer Courses, Yrs of Computer Experience, Computer Anxiety, Social Science			
3	.72	.52	.35
Number of Online Courses, Technical/Engineering, Business, Education, Science, Number of Computer Courses, Yrs of Computer Experience, Computer Anxiety, Social Science			
4	.72	.51	.37
Number of Online Courses, Business, Education, Science, Number of Computer Courses, Yrs of Computer Experience, Computer Anxiety, Social Science			
5	.72	.51	.39
Business, Education, Science, Number of Computer Courses, Yrs of Computer Experience, Computer Anxiety, Social Science			
6	.71	.50	.40
Business, Science, Number of Computer Courses, Yrs of Computer Experience, Computer Anxiety, Social Science			
7	.70	.49	.40
Business, Science, Yrs of Computer Experience, Computer Anxiety, Social Science			
8	.69	.48	.41
Business, Science, Computer Anxiety, Social Science			
9	.67	.44	.39
Business, Science, Social Science			

Summary

The analyses performed revealed that computer anxiety, computer self-efficacy, and computer experience did not predict successful performance in an online general education course. Additionally, it was found that gender and major did not significantly improve the ability of these variables to predict successful performance. Therefore, the null hypotheses for research question #1 were retained.

The multiple linear regression indicated that engagement in an online course can be predicted from computer anxiety, computer self-efficacy, and compute experience. However, computer anxiety was the only significant predictor of engagement when the other variables were statistically controlled. In addition, models including gender and academic major increased the amount of variance within engagement that could be predicted. A more thorough discussion of these results will be presented in Chapter 5.

CHAPTER 5. DISCUSSION, IMPLICATIONS, RECOMMENDATIONS

This chapter summarizes the results of the current research and provides a discussion regarding the findings and conclusions. The discussion also includes how the gaps in the previous body of knowledge were advanced. Limitations of the research and recommendations for future research are outlined.

Summary of the Results

This research was designed to provide additional information on how performance in online college courses may be impacted by computer anxiety, computer self-efficacy, and computer experience and address gaps in the current knowledge. The significance of this research is to add to the social cognitive theory body of knowledge and how the interaction between personal factors, environment, and behavior are evident in the online learning environment.

Past research has shown that computer anxiety, computer self-efficacy, and computer experience can impact performance (e.g., Abd-El-Fattah, 2005; Hauser et al., 2012; He & Freeman, 2010) and engagement (e.g., Fall & Roberts, 2012; Spence & Usher, 2007). However, these studies investigated the variables in computer-intensive courses or in other populations than the current research. This research filled a gap in the knowledge by examining how performance and engagement may be influenced by computer anxiety, computer self-efficacy, and computer experience in online general education college courses. Quantitative research methodology and design were utilized to answer the research questions. The analyses revealed that in this sample computer anxiety, computer self-efficacy, and computer experience did not significantly predict successful completion of online courses; however, these variables did significantly predict engagement in the online courses.

Discussion of the Results

The results of the hypothesis testing failed to reject the null hypothesis for the first research question and its subquestions. This was not expected since the published literature indicated that performance is often negatively impacted by high levels of computer anxiety and low levels of computer self-efficacy and computer experience (Abd-Ed-Fattah, 2005; Buche et al., 2007; Vician & Davis, 2002). However, in this sample, most of the participants successfully completed the previous online course and this may have influenced the results even though the sample met the assumptions for the analyses performed. For example, only 9.7% of the sample reported failing to successfully complete their online course.

The null hypothesis for the second research question was rejected. This indicated that computer anxiety, computer self-efficacy, and computer experience did predict engagement in the online course. Therefore, having this knowledge about a student at the beginning of a course could predict how engaged he or she would be in course activities. Although these three variables together predicted engagement the only variable that predicted engagement by itself was computer anxiety. Higher levels of computer anxiety were associated with lower scores on engagement. These results support earlier findings that high levels of computer anxiety can lead to more off-task cognitions (Smith & Caputi, 2001) and avoidance of complicated computer tasks (Shapka & Ferrari, 2003), consequently leading to less engagement. The prediction of engagement in online courses can be improved by knowing a student's gender and academic major.

Although all hypotheses were not supported and all findings were not as expected, this study answered the proposed research questions. The chosen methodology built upon the theoretical foundation of social cognitive theory to address the research problem and provide new information on how computer anxiety, computer self-efficacy, and computer experience may be impacting community college students in an online general education course.

Conclusions Based on the Results

This section will review the current findings within the foundations of Bandura's social cognitive theory (1977a). The results will be synthesized with the existing body of literature and its place within the literature defined. Interpretations of the research results will also be presented.

Comparison of the Findings with the Theoretical Framework and Literature

A basic tenet of social cognitive theory is "triadic reciprocal causation" (Bandura, 1989, p. 1175), or the interaction between personal characteristics, environment, and behavior. The broad body of research on social cognitive theory has presented evidence that anxiety and self-efficacy are domain-specific (Beelsey et al., 2010; Tay et al., 2006) and should be studied within specific context in order to understand their influence on behavior (Shu et al., 2011). The results of this study support the importance of understanding how personal factors, the environment, and behavior may interact in an online learning environment to impact the level of student performance and engagement.

Although the current research results failed to find a significant connection between computer anxiety, computer self-efficacy, computer experience, and performance, there is empirical evidence that suggests that a student's level of engagement is positively correlated with student success (Fall & Roberts, 2012). The current study's results indicated that individuals with higher levels of computer anxiety are less engaged in online courses. Taken together with Fall and Roberts (2012) findings, it is possible that computer anxiety impacts academic performance through its influence on engagement. For example, students having higher levels of computer anxiety are less engaged in course activities which leads to lower performance. Furthermore, Hirschfield and Gasper (2011) found that higher levels of engagement were linked with increased persistence and lower drop-out rates. Success in this study was defined according to grade earned; however, based upon these other findings, increased engagement may lead to academic success indirectly through persistence on difficult tasks and remaining enrolled. Persistence may be a key factor to the number of assignments completed in an online course. In other words, students with lower computer anxiety may be more actively engaged in their online courses which may lead to increased success and reduced dropout rates. This knowledge regarding the negative effects of computer anxiety may provide information to help reduce barriers to online education for students.

Interpretations of the Findings

These findings indicate that engagement in an online general education course can be predicted from computer anxiety, computer self-efficacy, and computer experience. In other words, knowing a student's levels of computer anxiety, computer self-efficacy, and computer experience at the beginning of a course would allow a prediction of how engaged, or involved, the student is likely to be in the course. This prediction could be made even if only the level of computer anxiety is known. This supported earlier findings presented previously that students with high levels of computer anxiety were off-task more often (Smith & Caputi, 2001).

Although these results failed to indicate that performance could be predicted from computer anxiety, computer self-efficacy, and computer experience, previous studies have documented a significant connection between these variables (e.g., Saadé & Kira, 2009). This may be due to the inherent differences between performance and engagement. Performance focuses on a single aspect of the course, which is grades. Engagement is a broader concept that involves not only the course work, but also a variety of interactions (student-faculty and peer interactions), as well as involvement with the learning management system. Some other factors that may impact performance are the specific course content and previous knowledge of the subject area.

Limitations

This research design was appropriate to answer the research questions; however, it also has limitations. Some of these limitations were known during the planning stage and were controlled to the extent they could be. For example, convenience sampling may have produced a sample that is not representative of the population. Also, using a survey method can lead to incomplete data cases or suffer from inaccurate information being provided. Extra participants were included in the sample to allow for potential incomplete data cases. In fact, there were incomplete data observed in the data set and this will be discussed in more detail below.

A critical limitation of the current study was the use of an online survey to measure comfort levels with a computer. Answering questions about one's comfort level with computers while using a computer may have increased awareness of the situational factor of computer use. However, it would have been prohibitive to survey geographically distant students in another manner. It is possible that some students who would have contributed valuable information to the study chose not to participate due to lack of confidence or discomfort with the delivery method. This may be the reasoning behind the number of cases with incomplete computer self-efficacy data and the lack of participants who endorsed high levels of computer anxiety. Also, there was a low number of participants who reported unsuccessful completion of the previous online course. It may be that students who were previously unsuccessful either chose not to participate or did not answer those questions.

Although the sample included more females than males, the data met the assumptions for the analyses performed; therefore, this was not considered a limitation. Also, there were several participants who did not complete all items for the Computer Self-efficacy Scale and were not included in those analyses. The items for the computer self-efficacy score were two-part questions. For these items participants were asked whether or not they were confident they could complete a certain task, then for affirmative answers they were asked to rate their level of confidence. This may have been confusing or intimidating for some participants and resulted in skipped questions. This was not considered a limitation since adequate power was demonstrated.

The distribution of scores within this sample appears to have deviated from a normal distribution. This limitation demands that the results be interpreted carefully. It must be understood that these results may not generalize to other samples of college students.

Another limitation of the methodology used is that causation cannot be inferred from the results. The methodology provided information about correlations between variables, and even about predictive relationships. However, interpretations of the results cannot assume that predictor variables caused the outcomes.

Despite these limitations, the data met the assumptions for the analyses performed and some of the hypotheses were supported. However, it is unknown what impact the missing data may have had.

Implications for Practice

This research adds to the body of knowledge on computer anxiety, computer self-efficacy, and computer experience and how they may impact performance and engagement in the online learning environment. Due to the high drop-out rate of adult learners (Shea & Bidjerano, 2016) and the increasing popularity of online education (Greenland & Morre, 2014), the identification of any potential barriers to students will be beneficial. Students may benefit from this knowledge by the implementation of procedures and/or support services to reduce their anxiety and increase their level of confidence.

Since high levels of computer anxiety were predictive of lower levels of engagement, providing extra support for students early in a course and incorporating opportunities for early success, which could lower computer anxiety may increase student engagement throughout the course. Knowledge about a student's experience with specific computer tasks could identify potential areas of increased computer anxiety. Resources could then be provided to students for assistance with unfamiliar tasks.

Recommendations for Further Research

The following recommendations may address the limitations of the current research and provide further knowledge in addressing the research problem. These recommendations include varying the format and recruitment methods to ensure a representative sample from the population. Additionally, it is recommended that a larger sample of college students be surveyed.

The use of a different format, rather than an online survey, may have produced a more varied sample. The current sample included no participants endorsing high levels of computer anxiety and a very low percentage endorsing low levels of computer self-efficacy. The use of a paper and pen survey may have attracted some of the volunteers who chose not to participate in an online survey. Additionally, few of the participants reported being unsuccessful in the previous online course. It would be desirable to have responses from more students who had been previously unsuccessful in an online course because their lack of success may have been impacted by high levels of computer anxiety and low levels of computer self-efficacy.

This sample of participants had some deviations from a normal distribution. This may have compromised the integrity of some analyses. It is recommended that data be collected from a larger sample which may provide more normally distributed data.

The current research collected performance data from a single course from the previous semester; however, a more detailed academic history might be informative, for example grade point average. Participant confidentiality prevented the collection of data from the institution; therefore, participants self-reported their grade from an online course the previous semester. It could have been the case that participants reported inaccurate data. An examination of computer anxiety, computer self-efficacy, and computer experience in an experimental design using repeated measures with the implementation of a program designed to reduce computer anxiety and increase computer self-efficacy might provide valuable knowledge.

While these results did not reveal a prediction of performance from computer anxiety, computer self-efficacy, and computer experience, the literature review revealed a connection between these variables in a sample including participants reporting high levels of computer anxiety (Buche et al., 2007). Therefore, a sample that included participants endorsing higher levels of computer anxiety, lower levels of computer self-efficacy, and unsuccessful completion of an online course as suggested above may provide more information about this possible connection.

Persistence was not specifically addressed in this study and future studies might also want to be examine it in more detail. The only direct link to persistence in this study was that unsuccessful course completion included any participants who withdrew from the online course. Since higher levels of engagement are associated with increased persistence and lower drop-out rates (Hirschfield and Gasper, 2011) investigating persistence along with computer anxiety, computer self-efficacy, and computer experience may provide important information. Persistence might be measured through number of assignments completed and/or amount of time spent working on assignments.

Conclusion

This research was founded upon the theoretical framework of social cognitive theory and the logical positivism of quantitative research methodology. It was designed to identify levels of computer anxiety, computer self-efficacy, and computer experience in an online community college population and determine if performance and engagement could be predicted. The results added to the body of knowledge in this area of research by indicating that performance could not be predicted by computer anxiety, computer self-efficacy, and computer experience. However, engagement could be predicted from computer anxiety, computer self-efficacy, and computer experience. Specifically, computer anxiety was predictive of engagement by itself when the other variables were controlled. Additionally, gender and academic major were also beneficial in a prediction of engagement in an online course. As with all research designs, this research had limitations which were addressed as practicality allowed. The remaining limitations have been outlined and recommendations for future research made. Further research in this area may help identify and reduce barriers to online education.

REFERENCES

Abd-El-Fattah, S. M. (2005). The effect of prior experience with computers, statistical self-efficacy, and computer anxiety on students' achievement in an introductory statistics course: A partial least squares path analysis. *International Education Journal, 5*(5), 71-79.

Alenezi, A. R., Abdul Karim, A. M., & Veloo, A. (2010). An empirical investigation into the role of enjoyment, computer anxiety, computer self-efficacy and internet experience in influencing the students' intention to use e-learning: A case study from Saudi Arabian governmental universities. *Turkish Online Journal of Educational Technology - TOJET*, *9*(4), 22-34.

Allen, I. E., Seaman, J., Poulin, R., & Straut, T. T. (2016, February). Online report card: Tracking online education in the United States. *Babson Survey Research Group.* Retrieved from http://onlinelearningsurvey.com/reports/onlinereportcard.pdf

American Association of Community Colleges. (2016). *Fast facts.* Retrieved from http://aacu.nche.edu.

American Psychological Association. (2010). *Ethical principles of psychologists and code of conduct*. Retrieved from http://www.apa.org/ethics/code/index.aspx.

Arning, K., & Ziefle, M. (2008). Development and validation of a computer expertise questionnaire for older adults. *Behaviour and Information Technology*, *27*(4), 325-329. doi:10.1080/01449290802127153

Bandura, A. (1977a). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191-215. doi:10.1037/0033-295X.84.2.191

Bandura, A. (1977b). *Social learning theory.* Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122-147. doi:10.1037/0003-066X.37.2.122

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1989). Human agency in social cognitive theory. *American Psychologist*, *44*(9), 1175-1184.

Bandura, A. (1997). *Self-efficacy: The exercise of control.* New York: W. H. Freeman and Co.

Bandura, A., & Cervone, D. (1983). Self-evaluative and self-efficacy mechanisms governing the motivational effects of goal systems. *Journal of Personality and Social Psychology, 45*(5), 1017-1028. doi:10.1037/0022-3514.45.5.1017

Bandura, A., & Locke, E. A. (2003). Negative self-efficacy and goal effects revisited. *Journal of Applied Psychology, 88*(1), 87-99. doi:10.1037/0021-9010.88.1.87

Baron, A., Kaufman, A., & Stauber, K. A. (1969). Effects of instructions and reinforcement-feedback on human operant behavior maintained by fixed-interval reinforcement. *Journal of the Experimental Analysis of Behavior, 12*(5), 701-712. doi:10.1901/jeab.1969.12-701

Beaudry, A., & Pinsonneault, A. (2010). The other side of acceptance: Studying the direct and indirect effects of emotions on information technology use. *MIS Quarterly*, *34*(4), 689-A3.

Beckers, J. J., & Schmidt, H. G. (2001). The structure of computer anxiety: A six-factor model. *Computers in Human Behavior, 17*, 35-49.

Beesley, A., Clark, T., Barker, J., Germeroth, C., Apthorp, H., & Mid-continent Research for Education and Learning (McREL). (2010). *Expeditionary learning schools: Theory of action and literature review of motivation, character, and engagement*. Denver, CO:Mid-continent Research for Education and Learning (McREL).

Belmont Report. (1979). *The Belmont Report: Ethical principles and guidelines for the protection of human subjects of research*. Retrieved from http://www.hhs.gov/ohrp/humansubjects/guidance/ belmont.html

Bilge, F., Tuzgol Dost, M., & Cetin, B. (2014). Factors affecting burnout and school engagement among high school students: Study habits, self-efficacy beliefs, and academic success. *Educational Sciences: Theory and Practice, 14*(5), 1721-1727. doi: 10.12738/estp.2014.5.1727

Birgin, O., Çatlıoğlu, H., Gürbüz, R., & Aydın, S. (2010). Investigation of the computer experiences and attitudes of preservice mathematics teachers: New evidence from Turkey. *Cyberpsychology, Behavior, and Social Networking*, *13*(5), 571-576. doi:10.1089/cyber.2009.0345

Bozionelos, N. (2001a). Computer anxiety: relationship with computer experience and prevalence. *Computers in Human Behavior, 17,* (2), 213-224

Bozionelos, N. (2004a). Computer Experience Scale. *Psyctests*, doi:10.1037/t25789-000

Bozionelos, N. (2004b). Socio-economic background and computer use: The role of computer anxiety and computer experience in their relationship. *International Journal of Human-Computer Studies, 61*(5), 725-746. doi: 10.1016/j.ijhcs.2004.07.001

Brand, J. L. (1996). Can we decide between logical positivism and social construction views of reality? *American Psychologist*, *51*(6), 652-653. doi:10.1037/0003-066X.51.6.652

Brosnan, M. (1998). The impact of computer anxiety and self-efficacy upon performance. *Journal of Computer Assisted Learning*, *14*(3), 223.

Buche, M. W., Davis, L. R., & Vician, C. (2007). A longitudinal investigation of the effects of computer anxiety on performance in a computing-intensive environment. *Journal of Information Systems Education*, *18*(4), 415-423.

Buelow, M. T., & Barnhart, W. R. (2017). The influence of math anxiety, math performance, worry, and test anxiety on the Iowa Gambling Task and Balloon Analogue Risk Task, *Assessment, 24*(1), 127-137. doi: 10.1177/1073191115602554

Burgos, J. E. (2007). The theory debate in psychology. *Behavior and Philosophy, 35*, 149-183.

Celik, V., & Yesilyurt, E. (2013). Attitudes to technology, perceived computer self-efficacy and computer anxiety as predictors of computer supported education. *Computers & Education*, *60,* 148-158. doi:10.1016/j.compedu.2012.06.008

Chua, S. L., Chen, D, & Wong, A. F. L. (1999). Computer anxiety and its correlates: A meta-analysis. *Computers in Human Behavior, 15*(5), 609-623. doi:10.1016/S0747-5632(99)00039-4.

Cohen, J. (2016). A power primer. In A. E. Kazdin, A. E. Kazdin (Eds.), *Methodological issues and strategies in clinical research, 4th ed* (pp. 279-284). Washington, DC, US: American Psychological Association. doi:10.1037/14805-018

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, *19*(2), 189-211.

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology. *MIS Quarterly*, *23*(2), 145-158.

Conrad, A. M., & Munro, D. (2008). Relationships between computer self-efficacy, technology, attitudes and anxiety: Development of the Computer Technology Use Scale (CTUS). *Journal of Educational Computing Research*, *39*(1), 51-73.

Daniels, L. R., Boehnlein, J. K., & McCallion, P. (2015). Life-review and PTSD community counseling with two groups of Vietnam War veterans. *Traumatology*, *21*(3), 161-171. doi:10.1037/trm0000045

Davis, J. (2009). Complementary research methods in humanistic and transpersonal psychology: A case for methodological pluralism. *The Humanistic Psychologist*, *37*(1), 4-23. doi:10.1080/08873260802394475

Deryakulu, D., & Çalışkan, E. (2012). A twin study of computer anxiety in Turkish adolescents. *Cyberpsychology, Behavior, and Social Networking*, *15*(4), 212-218. doi:10.1089/cyber.2011.0499

Desai, M. S. (2001). Computer anxiety and performance: An application of a change model in a pedagogical setting. *Journal of Instructional Psychology*, *28*(3), 141-149.

Elie-Dit-Cosaque, C., Pallud, J., & Kalika, M. (2011). The influence of individual, contextual, and social factors on perceived behavioral control of information technology: A field theory approach. *Journal of Management Information Systems*, *28*(3), 201-234.

Fagan, M. H., Neill, S., & Wooldridge, B. R. (2003). An empirical investigation into the relationship between computer self-efficacy, anxiety, experience, support and usage. *Journal of Computer Information Systems*, *44*(2), 95-104.

Fall, A. M., & Roberts, G. (2012). High school dropouts: Interactions between social context, self perceptions, school engagement, and student dropout. *Journal of Adolescence*, *35*(4), 787-798.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*, 175-191.

Fedotova,O., Teixeira, L., & Alvelos, H. (2013). Software effort estimation with multiple linear regression: Review and practical application. *Journal of Information Science and Engineering*, *29*, 925-945.

Finch, H., & Schneider, M. K. (2007). Classification accuracy of neural networks vs. discriminant analysis, logistic regression, and classification and regression trees: Three- and five-group cases. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, *3*(2), 47-57. doi:10.1027/1614-2241.3.2.47

Fontenot, R. J., Mathisen, R. E., Carley, S. S., & Stuart, R. S. (2015). Predictors of enrolling in online courses: An exploratory study of students in undergraduate marketing courses. *Journal of Educators Online*, *12*(1), 116-139.

Fuller, J. A., Stanton, J. M., Fisher, G. G., Spitzmüller, C., Russell, S. S., & Smith, P. C. (2003). A lengthy look at the daily grind: Time series analysis of events, mood, stress, and satisfaction. *Journal of Applied Psychology*, *88*(6), 1019-1033. doi:10.1037/0021-9010.88.6.1019

Fuller R, Vician C, & Brown S. (2006). E-learning and individual characteristics: The role of computer anxiety and communication apprehension. *Journal of Computer Information Systems*, *6*(4):103-115.

Funder, D. C. (1991). Global traits: A Neo-Allportian approach to personality. *Psychological Science, 2*(1), 31-39.

Geiser, C., Litson, K., Bishop, J., Keller, B. T., Burns, G. L., Servera, M., & Shiffman, S. (2015). Analyzing person, situation and person × situation interaction effects: Latent state-trait models for the combination of random and fixed situations. *Psychological Methods, 20*(2), 165-192. doi:10.1037/met0000026

George, D., & Mallery, P. (2014). *IBM SPSS Statistics 21 Step by Step* (13^{th} ed.). Boston, MA: Pearson.

Govaerts, S., & Grégoire, J. (2008). Development and construct validation of an academic emotions scale. *International Journal of Testing*, *8*(1), 34-54.

González, A., Fernández, M. C., & Paoloni, P. (2017). Hope and anxiety in physics class: Exploring their motivational antecedents and influence on metacognition and performance. *Journal of Research in Science Teaching, 54*(5), 558-585.

Greenland, S. J., & Moore, C. (2014). Patterns of student enrolment and attrition in Australian open access online education: A preliminary case study. *Open Praxis, 6*(1), 45-54.

Guthrie, J. T., & Klauda, S. L. (2014). Effects of classroom practices on reading comprehension, engagement, and motivations for adolescents. *Reading Research Quarterly*, *49*(4), 387-416.

Hank, P. (2015). Beyond an informal everyday concept of self-esteem. *Journal of Individual Differences, 36*(4), 237-246. doi: 10.1027/1614-0001/a000181

Harkness, S. (1992). Cross-cultural research in child development: A sample of the state of the art. *Developmental Psychology*, *28*(4), 622-625. doi:10.1037/0012-1649.28.4.622

Hashim, R., Ahmad, H., & Abdullah, C. Z. (2010). Assessing the attitudes of distance learners toward the use of ICT in education. *Turkish Online Journal of Distance Education, 11*(2), 125-134.

Hauser, R., Paul, R., & Bradley, J. (2012). Computer self-efficacy, anxiety, and learning in online versus face to face medium. *Journal of Information Technology Education: Research*, *11*, 141-154.

Havelka, D., Beasley, F., & Broome, T. (2004). A study of computer anxiety among business students. *Mid-America Journal of Business, 19*(1), 63-71.

He, J., & Freeman, L. A. (2010). Understanding the formation of general computer self-efficacy. *Communications of the Association for Information Systems*, *26*, 225-244.

Hebb, D. O. (1955). Drives and the C. N. S. (conceptual nervous system). *Psychological Review, 62*(4), 243-254. doi:10.1037/h0041823

Hergenhahn, B. R. & Henley, T. B. (2014) *An introduction to the history of psychology* (7th ed.). Belmont, CA: Wadsworth.

Hirschfield, P. J., & Gasper, J. (2011). The relationship between school engagement and delinquency in late childhood and early adolescence. *Journal of Youth Adolescence, 40,* 3-22.

Horowitz, J. E., & McCaffrey, R. J. (2008). Effects of a third party observer and anxiety on tests of executive function. *Archives of Clinical Neuropsychology, 23*, 409-417. doi: 10.1016/j.acn.2008.02.002

Kay, R. H. (1993). A practical research tool for assessing ability to use computers: The Computer Ability Survey (CAS). *Journal of Research on Computing in Education, 26*(1), 16-27.

Kay, R. (2006). Addressing gender differences in computer ability, attitudes, and use: The laptop effect. *Journal of Educational Computing Research, 34*(2), 187-211.

Keller, H., & Karau, S. J. (2013a). Online Course Impressions Instrument [Database record]. Retrieved from PsycTESTS. doi: http://dx.doi.org/10.1037/t26423-000

Keller, H., & Karau, S. J. (2013b). The importance of personality in students' perceptions of the online learning experience. *Computers in Human Behavior, 29*(6), 2494-2500. doi: 10.1016/j.chb.2013.06.007

Kirsch, F., Rohlf, H., & Krahé, B. (2015). Measuring anger regulation in middle childhood through behavioural observation: A longitudinal validation. *European Journal of Developmental Psychology, 12*(6), 718-727. doi:10.1080/17405629.2015.1101375

Lee, C., & Huang, M. (2014). The influence of computer literacy and computer anxiety on computer self-efficacy: The moderating effect of gender. *Cyberpsychology, Behavior, and Social Networking, 17*(3), 172-180. doi:10.1089/cyber.2012.0029

Leedy, P. D., & Ormrod, J. E. (2013). *Practical research: Planning and design* (10th ed.). Upper Saddle River, NJ: Pearson.

Lemke, M. K., Apostolopoulos, Y., Hege, A., Sönmez, S., & Wideman, L. (2016). Understanding the role of sleep quality and sleep duration in commercial driving safety. *Accident Analysis and Prevention, 97*, 79-86. doi:10.1016/j.aap.2016.08.024

Liu, S., Gomez, J., Khan, B., & Yen, C. (2007). Toward a learner-oriented community college online course dropout framework. *International Journal on E-Learning, 6*(4), 519-542.

Locke, E. A., Frederick, E., Lee, C., & Bobko, P. (1984). Effect of self-efficacy, goals, and task strategies on task performance. *Journal of Applied Psychology*, *69*(2), 241-251. doi:10.1037/0021-9010.69.2.241

López-Bonilla, J. M., & López-Bonilla, L. M. (2012). Validation of an information technology anxiety scale in undergraduates. *British Journal of Educational Technology*, *43*(2), E56-E58. doi:10.1111/j.1467-8535.2011.01256.x

Mabweazara, S. Z., Leach, L., & Andrews, B. S. (2017), Predicting swimming performance using state anxiety. *South African Journal of Psychology*, *47*(1), 110-120. doi: 10.1177/0081246316645060

Marakas, G. M., Yi, M. Y., & Johnson, R. D. (1998). The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. *Information Systems Research*, *9*(2), 126-163.

McCrae, R. R., & Costa, P. T., Jr. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, *52*(1), 81-90.

Merecz-Kot, D., & Andysz, A. (2017). Socio-demographic predictors of person-organization fit. *International Journal of Occupational Medicine and Environmental Health*, *30*(1), 133-145.

Miller, L. A., Stanney, K. M., & Wooten, W. (1997). Development and evaluation of the windows computer experience questionnaire (WCEQ). *International Journal of Human-Computer Interaction*, *9*(3), 201.

Motl, R. W., McAuley, E., & Klaren, R. (2014). Reliability of physical-activity measures over six months in adults with multiple sclerosis: Implications for designing behavioral interventions. *Behavioral Medicine, 40*, 29-33. doi: 10.1080/08964289.2013.821966

Nguyen, Q., Rienties, B., Toetenal, L., Ferguson, R., & Whitelock, D. (2017). Examining the designs of computer-based assessment and its impact on student engagement, satisfaction and pass rates. *Computers in Human Behavior*, *77*, 1-12.

O'Neil, H. J., Spielberger, C. D., & Hansen, D. N. (1969). Effects of state anxiety and task difficulty on computer-assisted learning. *Journal of Educational Psychology*, *60*(5), 343-350. doi:10.1037/h0028323

Palaigeorgiou, G. E., Siozos, P. D., Konstantakis, N. I., & Tsoukalas, I. A. (2005). A computer attitude scale for computer science freshmen and its educational implications. *Journal of Computer Assisted Learning*, *21*(5), 330-342. doi:10.1111/j.1365-2729.2005.00137.x

Park, J., & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Educational Technology & Society, 12*(4), 207-217.

Pouratashi, M., Zhub, C., Mohammadi, H. M., Rezvanfara, A., & Hosseinia, S. M. (2013). Effects of agricultural students' self-efficacy beliefs and test anxiety on their achievement motivation and academic performance. *New Educational Review*, *34*(4), 85-98.

Raub, A. C. (1981). Computer Anxiety Rating Scale. *Psyctests,* doi:10.1037/t13631-000

Rezaei, F., Ramaghani, N. A. H., & Fazio, R. L. (2017). The effect of a third party observer and trait anxiety on neuropsychological performance: The attentional control theory(ACT) perspective. *The Clinical Neuropsychologist, 31*(3), 632-643. doi: 10.1080/13854046.2016.1266031

Rogers, B. (1995). Critically evaluating research studies. *AAOHN Journal, 43*(1), 54-55.

Rovai, A. P. (2003). In search of higher persistence rates in distance education online programs. *Internet and Higher Education, 6*, 1-16.

Saadé, R. G., & Kira, D. (2009). Computer anxiety in e-learning: The effect of computer self-efficacy. *Journal of Information Technology Education*, *8*, 177-191.

Sam, H. K., Othman, A. A., & Nordin, Z. S. (2005). Computer self-efficacy, computer anxiety, and attitudes toward the internet: A study among undergraduates in Unimas. *Educational Technology & Society*, *8*(4), 205-219.

Schlosberg, H. (1954). Three dimensions of emotion. *Psychological Review*, *61*(2), 81-88. doi:10.1037/h0054570

Shapka, J. D., & Ferrari, M. (2003). Computer-related attitudes and actions of teacher candidates. *Computers in Human Behavior, 19*, 319-334.

Shea, P., & Bidjerano, T. (2016). A national study of differences between online and classroom-only community college students in time to first associate degree attainment, transfer, and dropout. *Online Learning*, *20*(3), 14-25.

Shepherd, B. E., & Yu, C. (2011). Accounting for data errors discovered from an audit in multiple linear regression. *Biometrics, 67*, 1083-1091. doi: 10.111/j.1541-0420.2010.01543.x

Shu, Q., Tu, Q., & Wang, K. (2011). The impact of computer self-efficacy and technology dependence on computer-related technostress: A social cognitive theory perspective. *International Journal of Human-Computer Interaction, 27*(10), 923-939. doi: 10.1080/10447318.2011.555313

Smith, B., & Caputi, P. (2001). Cognitive interference in computer anxiety. *Behaviour & Information Technology*, *20*(4), 265-273. doi:10.1080/01449290110069392

Spence, D. J., & Usher, E. L. (2007). Engagement with mathematics courseware in traditional and online remedial learning environments: Relationship to self-efficacy and achievement. *Journal of Educational Computing Research*, *37*(3), 267-288. doi:10.2190/EC.37.3.c

Sripada, R. K., Bohnert, K. M., Ganoczy, D., Blow, F. C., Valenstein, M., & Pfeiffer, P. N. (2016). Initial group versus individual therapy for posttraumatic stress disorder and subsequent follow-up treatment adequacy. *Psychological Services*, *13*(4), 349-355. doi:10.1037/ser0000077

Stal, C., Briese, C, De Maeyer, P., Dorninger, P., Nuttens, T., Pfeifer, N., & De Wulf, A. (2014). Classification of airborne laser scanning point clouds based on binomial logistic regression analysis. *International Journal of Remote Sensing*, *35*(9), 3219-3236. doi: 10.1080/01431161.2014.904973

Stowell, J. R., Allan, W. D., & Teoro, S. M. (2012). Emotions experienced by students taking online and classroom quizzes. *Journal of Educational Computing Research*, *47*(1), 93-106.

Sussman, T. J., Szekely, A., Hajcak, G., & Mohanty, A. (2016) It's all in the anticipation: How perception of threat is enhanced in anxiety. *Emotion*, *16*(3), 320-327. doi: 10.1037/emo0000098

Tay, C., Ang, S., & Van Dyne, L. (2006). Personality, biographical characteristics, and job interview success: A longitudinal study of the mediating effects of interviewing self-efficacy and the moderating effects of internal locus of causality. *Journal of Applied Psychology*, *91*(2), 446-454. doi:10.1037/0021-9010.91.2.446

Turner, J. S., & Leach, D. J. (2010). Experimental evaluation of behavioral activation treatment of anxiety (BATA) in three older adults. *International Journal of Behavioral Consultation and Therapy*, *6*(4), 373-394. doi:10.1037/h0100917

Vazire, S., & Mehl, M. R. (2008). Knowing me, knowing you: The accuracy and unique predictive validity of self-ratings and other-ratings of daily behavior. *Journal of Personality and Social Psychology*, *95*(5), 1202-1216. doi:10.1037/a0013314

Vician, C., & Davis, L. R. (2002). Investigating computer anxiety and communication apprehension in a computing-intensive learning environment. *Journal of Computer Information Systems*, *43*(2), 51.

Wang, R., Ryu, H., & Katuk, N. (2015). Assessment of students' cognitive-affective states in learning within a computer-based environment: Effects on performance. *Journal of Information & Communication Technology*, *14*, 153-176.

Warner, R. M. (2013). *Applied statistics: From bivariate through multivariate techniques* (2^{nd} ed.). Thousand Oaks, CA: Sage.

Wild, K. V., Mattek, N. C., Maxwell, S. A., Dodge, H. H., Jimison, H. B., & Kaye, J. A. (2012a). Computer Anxiety Survey. *Psyctests*, doi:10.1037/t28757-000

Wild, K. V., Mattek, N. C., Maxwell, S. A., Dodge, H. H., Jimison, H. B., & Kaye, J. A. (2012b). Computer-related self-efficacy and anxiety in older adults with and without mild cognitive impairment. *Alzheimer's & Dementia, 8*, 544–552.

Wilfong, J. D. (2006). Computer anxiety and anger: The impact of computer use, computer experience, and self-efficacy beliefs. *Computers in Human Behavior, 22*(6), 1001-1011.

Wintre, M. G., & Bowers, C. D. (2007). Predictors of persistence to graduation: Extending a model and data on the transition to university model. *Canadian Journal of Behavioural Science, 39*(3), 220-234. doi: 10.1037/cjbs2007017

Wood, R., & Bandura, A. (1989). Impact of conceptions of ability on self-regulatory mechanisms and complex decision making. *Journal of Personality and Social Psychology*, *56*(3), 407-415. doi:10.1037/0022-3514.56.3.407

Yadav, S., & Sharma, S. (2013). Co-relates between anxiety and academic achievement in teacher trainees. *Journal on School Educational Technology, 9*(2), 25-28

STATEMENT OF ORIGINAL WORK

Academic Honesty Policy

Capella University's Academic Honesty Policy (3.01.01) holds learners accountable for the integrity of work they submit, which includes but is not limited to discussion postings, assignments, comprehensive exams, and the dissertation or capstone project.

Established in the Policy are the expectations for original work, rationale for the policy, definition of terms that pertain to academic honesty and original work, and disciplinary consequences of academic dishonesty. Also stated in the Policy is the expectation that learners will follow APA rules for citing another person's ideas or works.

The following standards for original work and definition of *plagiarism* are discussed in the Policy:

> Learners are expected to be the sole authors of their work and to acknowledge the authorship of others' work through proper citation and reference. Use of another person's ideas, including another learner's, without proper reference or citation constitutes plagiarism and academic dishonesty and is prohibited conduct. (p. 1)
>
> Plagiarism is one example of academic dishonesty. Plagiarism is presenting someone else's ideas or work as your own. Plagiarism also includes copying verbatim or rephrasing ideas without properly acknowledging the source by author, date, and publication medium. (p. 2)

Capella University's Research Misconduct Policy (3.03.06) holds learners accountable for research integrity. What constitutes research misconduct is discussed in the Policy:

> Research misconduct includes but is not limited to falsification, fabrication, plagiarism, misappropriation, or other practices that seriously deviate from those that are commonly accepted within the academic community for proposing, conducting, or reviewing research, or in reporting research results. (p. 1)

Learners failing to abide by these policies are subject to consequences, including but not limited to dismissal or revocation of the degree.

Statement of Original Work and Signature

I have read, understood, and abided by Capella University's Academic Honesty Policy (3.01.01) and Research Misconduct Policy (3.03.06), including Policy Statements, Rationale, and Definitions.

I attest that this dissertation or capstone project is my own work. Where I have used the ideas or words of others, I have paraphrased, summarized, or used direct quotes following the guidelines set forth in the APA *Publication Manual*.

Learner name and date Beverly Pyle Barrett 8/23/18