Fall 12-14-2019

Computer Self-Efficacy, Digital Learners, and Completion Rates in the California Community College System

John R. Otte
Concordia University - Portland

Concordia University–Portland

College of Education

Doctorate of Education Program

WE, THE UNDERSIGNED MEMBERS OF THE DISSERTATION COMMITTEE

CERTIFY THAT WE HAVE READ AND APPROVE THE DISSERTATION OF

John R. Otte, Jr.

CANDIDATE FOR THE DEGREE OF DOCTOR OF EDUCATION

Donna Graham, Ph.D., Faculty Chair Dissertation Committee

Jean Swenk, Ph.D., Content Specialist

Michael Hollis, Ph.D., Content Reader

Computer Self-Efficacy, Digital Learners, and Completion Rates in the California Community College System

John R. Otte, Jr.

Concordia University–Portland

College of Education

Dissertation submitted to the Faculty of the College of Education

in partial fulfillment of the requirements for the degree of

Doctor of Education in

Higher Education

Donna Graham, Ph.D., Faculty Chair Dissertation Committee

Jean Swenk, Ph.D., Content Specialist

Michael Hollis, Ph.D., Content Reader

Concordia University–Portland

2019

Abstract

The importance of online learning in higher education has increased considerably over the last two decades. As a result, online learning has become an important area of research. The purpose of the study was to examine if higher levels of computer self-efficacy (CSE) contributed to online course completion among online California community college students. Guided by Bandura's (1977) work on self-efficacy and the work of Compeau and Higgins (1995) and Howard (2014) on computer self-efficacy, this study revealed that there is no relationship between high levels of CSE and successful completion of the course. A judgement sample was used to select five online sections from a northern California community college in which 122 students participated. These students completed a Computer User Self-efficacy questionnaire which consisted of 12 questions on a six-point Likert scale as well as three questions regarding their perceived use of computers. Spearman's Correlation Coefficient was conducted to see if a relationship existed between high levels of computer self-efficacy and course grades. The results showed that there was no statistically significant relationship between high levels of computer self-efficacy and course grades. The implication of this study suggests that computer self-efficacy may not be an important factor for today's digital learner.

Keywords: academic success, computer self-efficacy, course completion, digital learner, grades, online education, self-efficacy

Dedication

This dissertation is dedicated to my family. To my wife whose unwavering love and devotion gave me the strength to see this study through. To my son, daughter, and daughter-in-law who listened to my complaints, gave me encouragement, and always made sure that the wine glass was full.

Acknowledgements

First, I would like to acknowledge my Lord and Savior Jesus Christ and the Concordia University system for providing an outlet for Christian scholars. I would like to acknowledge my committee members: Dr. Donna Graham, chair, Dr. Jean Swenk, and Dr. Michael Hollis. Dr. Graham provided unbelievable guidance during this process and always gave me hope. To my Pastor, Ron Youngdale and the members of Good Shephard Lutheran Church, I appreciate your prayers and the generous financial contribution over the course of this study. To my family and friends who listened to my complaints and provided support—you all made this process bearable. To my dear friend Liz Izrailov-Burkey who acted as my editor and saved me from grammatical embarrassment. To my colleague, mentor, and family friend, Dr. James Curl who provided statistical advice and offered suggestions. Finally, to my mother and father who never doubted.

Table of Contents

Chapter 4: Data Analysis and Results

Chapter 5: Discussion and Conclusion

List of Tables

List of Figures

Chapter 1: Introduction

Introduction to the Problem

Online learning plays a significant role in higher education. According to a 2017 report from the National Center for Education Statistics (NCES), in 2015 more than one quarter of all undergraduate students were enrolled in distance education courses with 12% of all undergraduates participating exclusively in distance education (McFarland et al., 2017). By 2023, the NCES projects that undergraduate enrollment in online courses will increase to over 20 million. However, while online education is gaining in popularity, academic institutions are perplexed by the high rates of attrition associated with online learning (Lee, 2015). Lee maintains that while many factors have been proposed to explain this, student motivation and responsibility play a key role. As a result of this, studies examining the role of self-efficacy in general and the role of computer self-efficacy (CSE) in particular with respect to online learning and course satisfaction have received growing attention (Dang, Zhang, Ravindran, & Osmonbekov, 2016; Lee, 2015; Prior, Mazanov, Meacheam, Heaslip, & Hanson, 2016).

According to Bandura (1997) self-efficacy "refers to beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (p. 3). In fact, control is a crucial aspect of being human and unless people believe they can produce a desired effect by their actions, they have little motivation to act. Bandura (1997) argued that people's lives are guided by their belief in their own self-efficacy, and if they believe that they are powerless to produce results, they would not attempt to make things happen. In fact, a person's sense of self-efficacy can have a profound influence on how one approaches tasks and accepts challenges (Chang et al., 2014). Self-efficacy influences our choices of activities and motivational level. It supports efficient analytic thinking necessary for rooting out predictive knowledge from a confusing situation. Self-efficacy also regulates our motivations by honing aspirations and allowing us to manage difficult tasks. This is important for students enrolled in online courses because they bear more responsibility for their learning.

The research on self-efficacy and online learning environments has been predominantly related to computers and students' confidence in using technology (Cai, Fan, & Du, 2017; Howard, 2014; Pellas, 2014; W. A. Zimmerman & Kulikowich, 2016). These studies also determined that the quality of the experience increased self-efficacy for computers resulting in an increase in future usage and had a direct impact on classroom performance (Hauser, Paul, & Bradley, 2012; W. A. Zimmerman & Kulikowich, 2016). Studies also show that increased self-efficacy is important when evaluating digital natives (Malinovski, Vasileva, Vasileva-Stojanovska, & Trajkovik, 2014).

The current generation of students served by California's Community College system is often referred to as *digital natives* (Prensky, 2001, 2012), which reflects their ease and familiarity with digital technology. However, Gallardo-Echenique, Marqués-Molías, Bullen, and Strijbos (2015) suggest that the concept of digital native is vague and lacks any clear definition. Additionally, they note that many high schoolers and first year college students lack the digital skills possessed by their older "digital teachers." As a result, Gallardo-Echenique et al. (2015) suggest using the term *digital learner*. For the purposes of this research, digital learner will be used.

Background, Context, History, and Conceptual Framework for the Problem

Traditionally, psychological theories for education stressed that learning was the result of direct experience. However, Bandura (1977) argued that learning can occur by observing other people's behavior and the consequences of that observed behavior. This idea became the foundation of social cognitive theory.

First articulated by Bandura (1977), social cognitive theory is founded on the idea that learning is influenced by cognitive, behavioral, and environmental factors (Bandura, 1991). Social cognitive theory maintains that individuals do not simply respond to external stimuli. Instead, people actively seek and interpret information (Nevid, 2009). Self-efficacy is a key component of social cognitive theory because it affects students' motivation and learning.

The application of self-efficacy to online learning spans over two decades. Yet, scholars continue to argue that more research is needed in the area of online learning, in particular the role of CSE in online learning (Alqurashi, 2016). Prensky (2001) argued that the digital native has been exposed to digital media since birth. But, Gallardo-Echenique et al. (2015) suggest that the digital skills and digital confidence of digital learners are lower than their digital teachers. As a result, it is unclear what role being a digital learner plays in CSE or if CSE is even a factor in the lives of today's digital learner. This complexity could bring into question the role CSE plays in online learning academic achievement. For the purpose of this study, CSE was examined and the extent, if any, which CSE played in online completion rates among online students in California community colleges.

Statement of the Problem

Online education has become an important mode of delivery for institutions of higher education. Research shows that an increase in students CSE results in higher levels of course satisfaction, higher grades, more motivation and a better attitude (Prior et al., 2016). Attitude and student satisfaction are important factors for measuring success in online courses. Research shows that positive student attitude and student satisfaction results in higher student self-efficacy

(Prior et al., 2016). The purpose of this study was to examine if higher levels of CSE contribute academic success in online courses in California community colleges. In this quantitative correlational study Computer User Self-efficacy (CUSE) Scale and final course grades were the data sources.

Purpose of the Study

The purpose of this study was to examine if higher levels of CSE contributes to online course completion among online California community college students. For the purpose of this research, course completion will be defined as those students who pass their online course with a C or better. Additionally, the researcher will use a 12-item CUSE Scale. This scale was administered in the form of a questionnaire and used to determine their level of CSE. At the end of the term, the student's level of CSE was compared to their final course grade.

Research Question

The following research question guided this study:

RQ1. To what extent is there a relationship between higher levels of computer self-efficacy and the completion of online courses in California community colleges?

Hypothesis

H_o: There is no relationship between higher levels of computer self-efficacy and completion of online courses in California community colleges.

H_a: There is a positive relationship between higher levels of computer self-efficacy and the completion of online courses in California community colleges.

Rationale, Relevance, and Significance of the Study

A quantitative correlational design was used for this study to examine if a relationship existed between higher levels of CSE and course completion. Correlational research requires a data set to determine the existence of a relationship between two or more quantifiable variables and the extent of that relationship. When a selected range of scores in one variable is cognate to scores on other variables, there is evidence of a relationship. As a result, the researcher decided that correlational design would be the best method to adopt for this research.

As discussed above, it is important for this study to investigate the relationship between CSE and completion rates. This study attempted to ascertain the levels of CSE from three courses totaling five sections of sociology classes at a community college in California. Additionally, this study also examined if there was a relationship between the student's CSE score and their final course grade. This hypothesis testing process provided insightful information with respect to community college student's levels of CSE and the relationship with completion rates. It is hoped that this research will provide educators and online course developers with insight into the importance of CSE and the role that CSE plays in completion rates. Additionally, this research provided useful data in the debate regarding the role of CSE, completion rates, and the impact this as on digital natives.

Definition of Terms

Academic self-efficacy (ASE). This term refers to capabilities and confidence one has in her/his academic ability as it pertains to higher education (Jan, 2015).

Academic success. This term refers to the successful completion of a course with a grade of C or better.

California Community College system (CCC). The CCC is a postsecondary education system in California consisting of 114 community colleges.

Computer User Self-efficacy Scale (CUSE). The CUSE scale measures CSE as it pertains to online education (Howard, 2014).

Course completion. This term refers to completing an online course with a grade of C (70%) or better.

Computer self-efficacy (CSE). The capabilities and judgment of ones capability to use a computer (Compeau & Higgins, 1995).

Digital learner. This term refers to any student in the digital age who uses digital technology (Gallardo-Echenique et al., 2015).

Digital native. People born after 1980 who are competent users of technologies such as computers, mobile phones, video gaming devices, and the internet (Prensky, 2001, 2001b; Teo, 2016).

Online education. This term refers to courses offered exclusively over the Internet using web-based materials and activities made possible by various course management systems or other software packages (Meyer, 2014).

Retention rate. This term refers to students who stay in, and complete, a course.

Self-efficacy. Self-efficacy refers to the beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments (Bandura, 1997).

Success. This term refers to students who successfully complete a course with a grade of C (70%) or better.

Assumptions, Delimitations, and Limitations

All research possesses its own peculiarities. Leedy and Ormrod (2019) state, "assumptions are so basic that without them, the research problem itself could not exist" (p. 50). Assumptions are aspects of the research considered to be true. That is, the reader must assume that various aspects of the research are true with respect to population size, statistical test, research design, or other delimitations. The following assumptions are present in this study:

1. The researcher assumes that the use of the CUSE scale was adequate enough to measure the CSE of online students (Howard, 2014).
2. The researcher assumed that the respondents in the study were honest and truthful when answering the questionnaire.
3. The researcher is an adjunct faculty member on staff and assumed that some of the respondents might be former or present students.
4. The researcher also assumed that the number of survey respondents would be sufficient to apply the findings of the sample to the overall population.
5. The researcher assumed that instructors will be willing to participate and encourage their students to fill out the survey.
6. The researcher also assumed that students will have no concept of CSE but will have basic knowledge of computers and navigating online course platforms.

Delimitations are the boundaries set by the researcher and, therefore, within the control of the researcher (Leedy & Ormrod, 2019). They represent choices made by the researcher to set boundaries for the research. On the other hand, limitations occur due to influences that are out of the control of the researcher. They represent potential shortcomings, influences or other conditions that put restrictions on the methodology and conclusion of the research. Conversely, delimitations are within the control of the researcher. The following delimitations were present in this study:

1. Closed-ended short Likert scale were used in the survey. The objective is that more people would be willing to take and complete the survey. Additionally, the survey was only given to students enrolled in online courses given by the Social Sciences division at the California community college.

2. This research was also delimited by the semester chosen. Because institutional approval was given after the semester started, it was necessary to use late-start spring (March-May) and summer courses (June-July).

3. Online courses taught by the researcher were not included in this research.

Limitations to the study were as follows:

1. Because this is an exploratory study, the results are meant to guide future research and provide insight into the relationship between CSE and completion rates in online students in the CCC system.

2. This research was limited to one California community college.

3. The researcher was limited by time. As a result, the late-start sessions for Spring 2019 and Summer 2019 courses were used. These short semesters were impacted and were limited by the number of courses offered and the number of students attending.

4. Another limitation of this research was that the researcher is employed at the research site. As a result, this might have affected the students' responses if they are aware of the researcher's involvement.

Summary

Online education has become an important component in higher education (Meyer, 2014). As of 2015, nationwide, more than one quarter of all undergraduates were enrolled in online courses (McFarland et al., 2017). Furthermore, 12% of all undergraduates are exclusively enrolled in online education (McFarland et al., 2017). The amount of students enrolled in online learning is staggering and this number is projected to increase (McFarland et al., 2017). However, despite the popularity of online courses attrition rates for these courses are high (Lee, 2015). Understanding this relationship is vital if want to adequately serve our online students.

In the context of online learning, self-efficacy is especially important. Online learning requires more discipline and experience in technology (Jan, 2015). Online learning is self-directed and requires more discipline on the part of the student. Because self-efficacy is concerned with a person's confidence in their abilities to complete certain tasks and reach specific goals it has huge implications for online educators. As a result, examining the self-efficacy of the students in online education has become an important measure. Furthermore, online learning requires the use of the Internet and technology. Therefore, having both academic and CSE is crucial to the success of the student (Jan. 2015). This makes self-efficacy studies vital in online education because they are seen as a predictor of student success and academic performance.

However, while there is considerable research on self-efficacy in general and CSE in particular, there is little discussion on the relationship between CSE and digital learners. That is, by their nature, digital learners already possess some computer related skills necessary for success in online courses. With this in mind, higher levels of CSE might not be a determining factor in online course completion rates.

The intention of this study was to examine the relationship between CSE and completion rates in online courses in the California community college system. The purpose of the research was to examine if higher levels of CSE are a factor in completion rates given that today's student are digital learners.

Chapter 2: Literature Review

Introduction to the Literature Review

Online learning plays a significant role in higher education. As such, factors such as student success, satisfaction, and completion rates are important features when considering course development. According to Pukkaew (2013) significant attention has been given to course development including education platforms and best practices. According to a 2017 report from the National Center for Education Statistics (NCES) McFarland et al. (2017) noted that in fall 2015 more than one quarter of all undergraduate students were enrolled in distance education courses with 12% of all undergraduates participating exclusively in distance education. By 2023, the NCES projects that undergraduate enrollment in online courses will increase over 20 million. Not surprisingly, recent research shows that online education is growing at a faster rate than traditional face-to-face (F2F) courses (Means, Toyama, Murphy, & Baki, 2013). According to Atchley, Wingenbach, and Akers (2013):

> Enrollment in online courses has outpaced overall university enrollment for the past several years. The growth of online courses does not appear to be slowing . . . from fall 2002 to fall 2007, online enrollments grew at a compound annual growth rate of 19.7% from 1.6 million to more than 3.9 million. (p. 104)

Furthermore, studies show that one-third of students have taken at least one online course over their academic career and most students have taken considerably more (Meyer, 2014). As a result, the significance and efficacy of online learning has been getting a lot of attention for at least 20 years.

However, while the popularity of online education is increasing, academic institutions are puzzled by the large number of students who do not complete their online courses. Factors such as responsibility and student motivation are said to play a role (Lee, 2015). Therefore, studied examining the role of course satisfaction in online learning have increased (Dang et al., 2016; Lee, 2015; Prior et al., 2016).

This chapter contains a discussion of the background to the problem, the conceptual framework, and a review of the literature, which covers the most recent research regarding self-efficacy and online learning. The search for information on retention utilized online databases such as ERIC, ERIC ProQuest, and ProQuest Dissertation and Theses Global, through the Concordia University Library, and Google Scholar. Keyword searches used included, academic achievement, academic self-efficacy (ASE), CSE, distance education, gender, online learning, and student satisfaction.

Background to the study

Self-efficacy "refers to beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p. 3). Each situation is context-specific and, therefore, self-efficacy beliefs will vary from person to person and situation to situation. As a result, self-efficacy beliefs must be considered carefully as situations change. For example changes in the delivery of education from traditional F2F coursed to online courses may affect the student's self-efficacy beliefs (Hodges, 2008; Jan, 2015).

While the literature on the application of self-efficacy to online learning spans over two decades, it is still in its infancy (Hodges, 2008) and more research is needed in the area of online learning (Alqurashi, 2016). Additionally, examining whether self-efficacy differs by gender has received little attention (London, 2016) and, what research has been done has been inconsistent. For example, while some studies argue that there is no statistical significance between online self-efficacy and gender (Al-Azawei & Lundqvist, 2015) others argue that there is differences between males and females with respect to self-efficacy (Shen, Cho, Tsai, & Marra, 2013). To complicate matters further self-efficacy can be examined in several arenas; for instance, there is ASE, CSE, Internet self-efficacy, and course content self-efficacy. However, this too has produced inconsistent results. Furthermore, there has been no study examining the relationship between digital learners and CSE. As a result, the relationship between digital learner and CSE will be examined.

Conceptual Framework

Understanding self-efficacy requires a foundation in the theoretical model associated with social cognitive theory. This theory has been used as theoretical frameworks for developing online learning environments in an effort to foster increased self-efficacy and to motivate students (Hodges, 2008). This section will explore the social cognitive theory of self-efficacy as articulated by (Bandura, 1977) and its relevance to the research problem. A review of the literature will be presented examining the different levels of self-efficacy and motivation among college students in online courses with particular attention to digital learners.

Social cognitive theory. Developed by Bandura, social cognitive theory is grounded on the idea that learning is influenced by cognitive, behavioral, and environmental factors (Bandura, 1991). Traditional psychological theories stressed that learning was the result of direct experience. However, Bandura speculated that nearly all learning phenomena can occur by observing other people's behavior and the consequences of that behavior (Bandura, 1986). Social cognitive theory argues that individuals do not simply respond to environmental stimuli. Instead they actively seek and interpret information (Nevid, 2009). Individuals "function as contributors to their own motivation, behavior, and development within a network of reciprocally interacting influences” (Bandura, 1997, p. 169). Self-efficacy is a key element of social cognitive theory because it affects students’ motivation and learning.

In the context of online learning, self-efficacy is especially important. Online learning is self-directed. It requires increased discipline on the part of the student. Self-efficacy is concerned with a person’s confidence in their abilities to complete certain tasks and reach specific goals (DeTure, 2004). As a result, self-efficacy studies are often seen as a predictor of student success and academic performance (Zimmerman, 2000).

Self-efficacy. According to Bandura (1997), self-efficacy “refers to beliefs in one’s capabilities to organize and execute the courses of action required to produce given attainments” (p. 3). In fact, control is a crucial aspect of being human and unless people believe they can produce a desired effect by their actions, they have little motivation to act. Bandura (1997) argued that people’s lives are guided by their belief in their own self-efficacy and if they believe that they are powerless to produce results, they would not attempt to make things happen. Furthermore, a person’s sense of self-efficacy can have a profound influence on how one approaches tasks and accepts challenges (Chang et al., 2014).

Bandura (1997) also makes clear that self-efficacy plays an important role in social cognitive theory. Self-efficacy influences our choices of activities and motivational level. It supports efficient analytic thinking necessary for rooting out predictive knowledge from a confusing situation. Self-efficacy also regulates our motivations by honing aspirations and allowing us to manage difficult tasks (Bandura, 1977, 1995, 1997). Bandura (1977) outlined four sources of information that individuals use to gauge their efficacy: performance outcomes, vicarious experiences, verbal persuasion, and physiological feedback. These four sources guide individuals as they determine whether or not they have the capability to accomplish specific tasks (Bandura, 1997). These characteristics are vital when considering the self-directed nature of online education.

Performance outcomes. According to Bandura, performance outcomes (past experiences) are the most important source of self-efficacy. Both positive and negative experiences can influence the ability of an individual to perform a given task. For example, if someone has performed well at a previous task then that person is more likely to feel proficient and perform well at a comparable task (Bandura, 1977). Bandura (1997) states,

> Enactive mastery experiences are the most influential source of efficacy information because they provide the most authentic evidence of whether one can muster whatever it takes to succeed. Success builds a robust belief in one's personal efficacy. Failures undermine it, especially if failures occur before a sense of efficacy is firmly established. (p. 80)

In the case of online learning performance outcomes student success increases if they have positive experiences with past online courses or with computer use in general.

Vicarious experiences. People can develop high or low self-efficacy vicariously through observing the actions of other people. For example, a person can watch someone in a similar position and then compare his or her own competence with the other individual's competence (Bandura, 1977). If a person sees someone similar to her/him succeed, it can raise their self-efficacy. However, seeing someone similar fail can lower one's self-efficacy. However, this factor can be problematic in online learning because students do not physically see or interact with each other. As a result, they are unable to identify other students who may also be struggling in task completion. However, when online instructors provide positive feedback in discussion forums, they are promoting vicarious experiences for learning.

Verbal persuasion. Through the use of suggestion and encouragement, people can be made to believe that they can accomplish a task or engage in specific behavior. Verbal persuasion can have an effect on self-efficacy. In this context, self-efficacy can be influenced by encouragement and discouragement with respect to an individual's ability to perform. For example, positive encouragement from a teacher can result in the student putting forth more effort, resulting in a greater chance at succeeding. Conversely, negative comments from a teacher can lead to self-doubt, resulting in lower changes for success. However, verbal persuasion is not a part of personal experiences. As a result, it is considered a poorer inducer of self-efficacy and therefore, it may be eclipsed by the individual's past failures (Zeb & Nawaz, 2016). However, verbal persuasion is directly connected with online learning in the sense that it helps to build a community. Research conducted by Nagel, Blignaut, and Cronjé (2009) shows that when online students are actively engaged in discussion forums by reading discussion posts and providing quality peer replies, a sense of community is established.

***Physiological feedback*.** Also referred to as emotional arousal, physiological feedback refers to the bodily sensations people experience and how this emotional arousal influences their beliefs of efficacy (Bandura, 1977). Examples of physiological feedback would include giving a presentation, making a public speech, or taking an exam. In every case, the person would experience bodily sensations such as anxiety, sweaty palms and, possibly, heart palpitations. While Bandura (1977) suggests that this element is the least influential of four, it is important to note that if one is calm and more at ease with a given task then the higher the self-efficacy beliefs. In the case of online learning, the students are putting themselves in the best possible scenario by being in a familiar environment (home) with less physical interaction.

Educators want their students to be successful. As online educators, this becomes especially difficult because of the lack of F2F interaction we have with our students and because students must possess both academic and CSE to be successful in online learning (Jan, 2015). Online learning requires that students use technology effectively. However, this does not mean that we cannot gauge their success. Self-efficacy has become an important tool for measuring success (Prior et al., 2016). Online learning is self-directed. Self-efficacy provides the framework for scholars to measure the success of our online students by measuring the confidence in their abilities to complete certain tasks and reach specific goals (DeTure, 2004). As a result, self-efficacy studies are often seen as a predictor of student success and academic performance.

Review of the Literature and Methodological Literature

The demand for online education has increased substantially over the last several decades. In fact, online education is growing at a faster rate than traditional F2F courses (Means et al., 2013). However, while the course content is the same, the delivery method is dramatically different. Online education requires more discipline and experience in technology (Jan, 2015). As a result, making sure that students have confidence and believe in their ability to be successful is vital and understanding the role of self-efficacy plays a major role in the successful completion of a subject (Vayre & Vonthron, 2017).

The research on self-efficacy and online learning environments has been predominantly related to computers and students' confidence in using technology (Zimmerman & Kulikowich, 2016). Studies show that perceived efficacy for using computers results in greater likelihood of people using them (Hodges, 2008). It was also determined that the quality of the experience increased self-efficacy for computers resulting in an increase in future usage (Hodges, 2008) and had a direct impact on classroom performance (Hauser et al., 2012). That is, positive performance and technology related self-efficacy is directly related to student performance in online classes (Zimmerman & Kulikowich, 2016) .

However, there are many variables in play when it comes to self-efficacy and online learning. For example, success in online learning requires both computer and academic self-efficacy. While research shows that females tend to be more successful in academic achievement over males (Voyer & Voyer, 2014), little research has been done regarding gender differences in online self-efficacy. Furthermore, what research has been done has produced mixed results (Jan, 2015). Therefore, this review will focus on the literature pertaining to self-efficacy and the relationship between academic achievement, CSE, student satisfaction, and gender differences.

Self-efficacy in online learning. College students engage in many tasks during their academic studies and no task is more apparent than the use of the Internet. Whether students are enrolled in traditional F2F courses or online classes, the Internet has become a necessary tool. In fact, research suggests that a vast majority of F2F courses utilize computer-based technology to some degree (McFarland et al., 2017). Principles of efficacy can encourage individuals to become committed and achieve desired outcomes successfully. Students who are confident in their abilities will have a strong sense of efficacy. These students do not take difficult tasks as obstacles to avoid but, instead, as a challenge to develop skills (Alqurashi, 2016). If they fail at a certain task, these students quickly regain their sense of efficacy. As a result, stress and anxiety are reduced and the amount of personal accomplishments is enhanced (Bandura, 1997).

As discussed previously, self-efficacy expectations are based on four major sources of information: performance outcomes, vicarious experiences, verbal persuasion, and physiological feedback. These four elements are the core principles for the development of self-efficacy in general, and they are specific to the learning context. Performance outcomes are the first source of information and are the most influential as it is based on the student's previous successful experience (Alqurashi, 2016). Repeated successes result in strong self-efficacy expectations, which, in turn, lead to reducing the negative affect of failure. Bandura (1997) states, "improvements in behavioral functioning transfer not only to similar situations but to activities that are substantially different from those which the treatment was focused" (p. 195). Unlike performance outcomes, in vicarious experiences students do not depend on their successful experiences as the main source of information. Instead, they observe others performing an activity successfully, and this can be valuable in forming beliefs in self-efficacy (Alqurashi, 2016). Bandura notes that learners "persuade themselves that if others can do it, they should be able to achieve at least some improvement in performance" (p. 197). As a result, it does not depend on someone's capability to achieve a task but on social comparison. This suggests that individual self-efficacy would increase if students are capable of achieving a task that others have done, and conversely, individual self-efficacy would decrease if the student failed to meet the performance of others (Alqurashi, 2016).

Verbal persuasion through encouragement can lead to higher levels of self-efficacy, while unrealistic feedback results in lower levels of self-efficacy (Alqurashi, 2016). Bandura (1997) notes, "Skilled efficacy builders encourage people to measure their success in terms of self-improvement rather that in terms of triumphs over others" (p. 106). Finally, psychological feedback is the last source of information that can have a direct effect on students' self-efficacy. People's level of stress and anxiety is dependent on one's physiological state. In general, people will be successful if they are not in a state of adverse physiological arousal (Alqurashi, 2016).

While online learners are similar to traditional F2F learners in terms of their self-efficacy (Lin, Liang, Yang, & Tsai, 2013) self-efficacy in the context of online learning is influenced previous success with online learning (performance outcomes), pre-course training (vicarious experiences), instructor feedback (verbal persuasion), and online learning technology anxiety (physiological feedback) (Bates & Khasawneh, 2007). Furthermore, self-efficacy beliefs depend on the surrounding context. As the situation changes so do the self-efficacy beliefs. For example, changes in the mode of deliver from F2F to online learning may affect student self-efficacy beliefs (Hodges, 2008). Online learning requires greater discipline because learning takes place at a distance away from the academic institution. Understanding student confidence and motivation becomes critical because online learning places the responsibility of learning on the student more so than does traditional F2F learning (Lee, 2015).

Research into self-efficacy started before the advent of online education. According to Hodges (2008), research into the self-efficacy of online learning is still its infancy and that more research is needed in the area of self-efficacy and online education. Much of the research has been conducted in higher education with upper division undergraduates and graduate students. While most of the focus of the literature has been on academic self-efficacy (Jan, 2015), other research has explored the technology factor of self-efficacy in online education, for example, Internet self-efficacy (Kuo, Walker, Schroder, & Belland, 2014; Lin et al., 2013), information seeking self-efficacy (Tang & Tseng, 2013), learning management system (LMS) self-efficacy (Martin, Tutty, & Su, 2010), learning factor (Hodges, 2008), and the multi-dimension of self-efficacy in online learning (DeTure, 2004; Miltiadou & Yu, 2000; Puzziferro, 2008; Shen et al., 2013). However, recent students have explored the importance of CSE (Jan, 2015; Pellas, 2014).

Aktürk (2014) investigated the relationship between self-efficacy beliefs and the educational use of the Internet and student epistemological beliefs. Epistemology is a subfield of philosophy that focuses on the nature and justification of human knowledge. As a result, epistemological studies can be an important component in studies on self-efficacy.

Aktürk (2014) examined 411 community college students in central Turkey. Demographic data included information on gender, class (e.g. freshman or sophomore), department, computer ownership, Internet access, and academic achievement level. The study group comprised 230 (56%) males and 181 (44%) females. Aktürk's data collection tools consisted of an Educational Internet Use Self-efficacy Beliefs Scale (EIUSEB) and an Epistemological Beliefs (EB) scale. Aktürk observed a negative relationship between EIUSEB and EB scale. This suggests that students who have sophisticated beliefs regarding the fact that learning is an activity that requires considerable effort also have higher EIUSEB. Also, with respect to gender Aktürk noticed that male students have higher EIUSEB than did females implying that males use the Internet more for educational purposes than do females. While this study does not measure the student's academic performance, it does measure the student's perception (epistemology) of how well they should perform, and technology and Internet access was vital.

Computer self-efficacy. CSE was first defined by Compeau and Higgins (1995) as "a judgment of human's capability to use a computer" (p. 192). Research on computer and self-efficacy mainly refers to student's confidence in their ability of using computers and other related technology. Being successful in online education requires the student to be effective with online technology. Online learning requires the student to have both academic and CSE. Bandura (1977) tells us that performance experience is one of the factors that impacts perceived self-efficacy. Research shows that prior computer training plays a significant role in helping to distinguish between students who completed online distance education courses and those who did not (Jan, 2015). In fact, several studies have found that CSE is higher for students who had prior training on computers or who had previously taken online courses (Jan, 2015; Lee, 2015; Zimmerman & Kulikowich, 2016). Students with higher levels of CSE are more likely to believe in the value of computer learning and that the use of computers for a large variety of tasks is effective in increasing the level of self-efficacy (Pellas, 2014). Furthermore, studies show that students with increased levels of CSE tend to spend more time using online learning technology and those students were more easily engaged in the learning process (Bates & Khasawneh, 2007).

Many studies have investigated the characteristics of individuals and their connection to technology in general and CSE in particular. In fact, gender differences in the attitude toward technology has been a growing concern in higher education (Cai et al., 2017). A recent meta-analysis shows that male students tend to have a more favorable attitude toward technology use than do female students. In fact, makes appear to be more confident and knowledgeable using technology-related media. The reasons for why these differences exist are not well known. But, scholars suggest that it could be due to the differences of individual psychology state, behaviors and motivations (Cai et al., 2017). Additionally, culture could play a key role considering that males still dominate the technology job sector (Cai et al., 2017).

Similarly, Bao, Xiong, Hu, and Kibelloh (2013b) explored the relationship between gender, CSE, and mobile technology, such as the use of smart phones. They suggested that males and females would vary considerably in what influences their CSE. They found that males and females viewed the usefulness of mobile technology similarly, but uncovered difference between them with regard to its perceived ease of use. That is, according to Bao et al. (2013b) males scored higher with respect to CSE, the perceived ease of use, and the behavioral intention to use mobile technology for learning.

Research into CSE has also investigated the relationship between gender, personality, psychological traits and psychological well-being. Saleem, Beaudry, and Croteau (2011) investigated the relationship between CSE and gender with respect to personal characteristics and their relationship to CSE. In particular, the researchers found distinct differences between gender with regard to personality traits and CSE, but generally indicated that open, extraverted, conscientious individuals tend to have higher CSE than their counterparts. Therefore, personality traits appear to play a significant role in CSE.

CSE also plays a significant role in facilitating the impact of anxiety on perceived ease of use (Achim & Al-Kassim, 2015; Saadé & Kira, 2009). Research shows that the more students incorporate computers into their work, the more confident they feel in handling the computer (Achim & Al-Kassim, 2015; Jan, 2015). In this regard, CSE reduces the strength and significance of the impact of anxiety on the perceived ease of computer use. Research by Pellas (2014) shows that higher levels of CSE resulted in higher levels of cognitive and emotional engagement and made the learning process easier.

Additionally, Bellini, Isoni Filho, de Moura Junior, and Pereira (2016) examined the relationship between anxiety and CSE with respect to an individual's use of mandatory technology new to the market. They suggest that there are several levels of CSE and anxiety. First, high levels of CSE and low levels of anxiety were "beneficial for mandatory technology use [but do] not necessarily promote voluntary technology use" (p. 55). Secondly, either extremely high CSE or lower levels of CSE can undermine the effectiveness of mandatory technology use. Equally, extremely low levels of anxiety and higher levels of anxiety can undermine the effectiveness of mandatory technology use.

CSE also plays a role in academic performance and course outcomes. While the role of academic performance is minor, research by Zimmerman and Kulikowich (2016) suggest that there is a slight positive correlation between CSE and student performance in online courses. With respect to course outcomes, the literature is inconsistent. While research by DeTure (2004) and Puzziferro (2008) suggest that CSE does not affect course outcomes, work by Wang, Shannon, and Ross (2013) does. In fact, their study actually examined the role of technology self-efficacy and determined that CSE alone is not enough and that it must be observed in concert with online learning self-efficacy. However, not everyone is convinced that perceived self-efficacy predicts success. Writing in 2008, Hodges stated, “Computer use is obviously important in successful completion of an online course, but self-efficacy for computer use in a general sense is most likely not as predictive of success in the course as a more specific measure” (p. 21). In fact, recent work by Wilson and Narayan (2016) suggests that task self-efficacy and self-regulated learning are better indicators of academic performance.

This more “multifaceted” approach for understanding the role of CSE is also examined by Shen et al. (2013) and they argue that this multifaceted approach for studying self-efficacy in online learning is necessary. They suggest that there are five dimensions of online learning self-efficacy: (a) self-efficacy to complete an online course, (b) self-efficacy to interact socially with classmates, (c) self-efficacy to handle tools in a Course Management System (CMS), (d) self-efficacy to interact with instructors in an online course, and (e) self-efficacy to interact with classmates for academic purpose. Shen et al. (2013) argue that online learning self-efficacy can be used to predict students’ online learning satisfaction.

Student satisfaction is another area of interest for CSE. Dang et al. (2016) showed that students with higher levels of self-efficacy tended to form more positive attitudes toward learning, were more willing to learn, and had overall more satisfaction. Additionally, their research highlighted some interesting gender differences. That is, higher levels of CSE for female students were shown to influence their perceived accomplishment and enjoyment. However, no such influence was found for male students. The role of gender in CSE will be addressed below.

CSE is also important with respect to organizational and productivity-related outcomes (Shao, Wang, & Feng, 2015). Those individuals with high levels of CSE tend to share knowledge in an organizational setting which has a positive effect on knowledge sharing, group culture, sharing, and trust (Shao, Wong, & Feng, 2015). Shao, Wong, and Feng (2015) examined CSE in two ways. First, they examined organizational cultures looking for connections between collaboration and openness and high levels of CSE. Second, they explored the relationship between individual employees with high CSE and their willingness to share knowledge with colleagues both tacitly and explicitly. The findings of this research uncovered CSE as an important mediator in the relationship between organizational culture and knowledge sharing, illustrating the connection between a culture of collaboration and teamwork, and increased confidence using and sharing knowledge about increasingly complicated systems in the workplace.

Academic achievement. The term *academic achievement* is one of the most widely used constructs in educational research (York, Gibson, & Rankin, 2015). It is the tool educators use to measure the success of our students. Within higher education it has become a catchall phrase encompassing many student outcomes with phrases like student satisfaction, acquisition of skills, persistence, attainment of learning outcomes, career success, student success and academic success (York et al., 2015). For the purpose of this research, academic achievement refers to a student's successful completion of a course with a C or higher.

Success in online learning environments relies on the student's ability to act autonomously and be actively engaged in the learning process (Broadbent & Poon, 2015). It is necessary for online students to be more independent and self-directed. Therefore, it is incumbent upon online students to have the self-generated ability to manage, control and plan their learning strategies. This form of self-regulated learning has played a crucial role in understand academic achievement. Research suggests that learning strategies like time management, metacognition, and effort regulation are significantly associated with academic achievement (Broadbent & Poon, 2015).

Positive and negative learner expectation towards online learning can also affect academic success. While research into learning expectation is new what research has been done shows that academic achievement in online education depends, in large part, on the students attitude for the learning environment, teaching method, and relationship between the student and educator (Erdogan, Bayram, & Deniz, 2008) In fact, the relationship between the student and the educator is vital for the self-efficacy of the student due to the importance of physiological feedback. Feedback provided by the educator is an important source of information to enhance and regulate the student's sense of self-efficacy which, in turn, promotes greater academic achievement (Goulão, 2014).

Learner agency also plays a key role in academic success and refers to the student's ability for self-directed engagement. Learner agency is self-directed engagement and refers to the capability of the student to make choices and act on those choice to make meaningful difference in their lives (Xiao, 2014). Developing student agency with respect to self-efficacy, identity, motivation, and metacognition is shown to contribute significantly to academic achievement (Xiao, 2014).

However, some research does suggest that there is no significant relationship between student self-efficacy and academic achievement. In fact, it is argued that in reality, self-efficacy is a component of self-esteem and that academic achievement can also be influenced by socio-economic status, learning styles, motivation, school related factors, and social behavior despite how much self-efficacy the student has (Balami, 2015). Academic achievement can also be influenced by environmental factors, conditions and other experiences. For example, Balami (2015) showed that high self-efficacy is not an indicator of academic success and that academic success was better explained by the social environment. That is, the social environment of Nigeria is not learner friendly due to the physical environment and the security challenges necessary as a result of the Boko Haram insurgency, which has been particularly difficult for females resulting is significant disparities between males and females in terms of self-efficacy and academic achievement. While this case study represents an extreme case for the role of self-efficacy in academic achievement, it emphasizes that academic achievement can also be influenced by other factors.

Modern approach to CSE. As technology becomes more complex, CSE continues to become more relevant in research and practical application. Howard (2014) noted that existing methods of CSE were deficient. He sought to develop a more modern instrument for today's CSE research. Howard identified multiple issues with existing CSE instruments prominently falling within three themes. First, some of the items in popular CSE instruments could be influenced by factors outside the realm of CSE, such as reading abilities, learning capacity, anxiety, or the context of computer use. Second, some elements in popular CSE instruments tend to measure technical skills rather than self-efficacy. As the definition of CSE addresses belief over ability, these items are misaligned. Finally, Howard notes that some items used to measure CSE are irrelevant and outdated. Instruments included items regarding obsolete technology such as floppy disks, mainframe systems, and DOS-based computer packages (p. 678).

In response to these issues, Howard (2014) developed a 12-item instrument through the process of exploratory and confirmatory factor analysis. The instrument was also tested for criterion validity against a well-known and popular existing CSE scale. The new instrument was reported to have "superb psychometric properties . . . excellent internal consistency . . . and seem[ed] to be a satisfactory tool for future research" (p. 680). This instrument provides an opportunity to investigate CSE in a modern context to continue to answer calls for future research with regard to CSE mediators, moderators, predictors, and outcomes. As a result, this scale will be employed in this research design.

The digital learner. The terms "digital native" and digital immigrant" were first articulated by Prensky (2001a, 2001b). Digital native refers to students generally born after 1980 who are native speakers of the digital language of computers, video games, the Internet, and mobile phones. These students received digital input while growing up, suggesting that their brains are now wired differently from digital immigrants. Digital immigrants are people born before 1980 that did not grow up with digital technology, but, instead, learned how to use the language of computers, gaming, the Internet, and mobile phones later in life.

Today's students use digital technologies and the Internet in all aspects of their daily life including school, work, and leisure activities (Gallardo-Echenique et al., 2015). In fact, they represent the first generation to grow up with this new technology, and they have spent most of their lives surrounded by digital communication technology. Gallardo-Echenique et al. (2015) note, “They use the Internet, text messaging, and social networking, but they are using these technologies primarily for social and entertainment purposes” (p. 157).

The digital native discourse was popularized by Prensky (2001a, 2001b) and emerged in the late 1990s and early 2000s. Many educators have uncritically accepted Prensky’s notion that there is a generation of learners who think differently due to their early exposure to and interaction with technology. Studies have explored digital native status with regard to consumer attitudes, digital messaging, and social media (Page, DK, & Mapstone, 2010; Verčič & Verčič, 2013; Yong & Gates, 2014). Digital natives have also received international attention (Kennedy & Fox, 2013). Educational research about digital natives has investigated technology use, integration, preferences, and confidence in educational settings (Kennedy & Fox, 2013). These studies have reported findings that support and refute Prensky’s original assertions about digital natives.

So, Choi, Lim, and Xiong (2012) cited digital native research when developing their hypotheses about new student teachers and whether their CSE changed their expectations of technology use in the classroom. The researchers sought to examine the intention of digital native teachers to integrate technology into their instruction. Their findings indicated that those digital native teachers who reported high CSE along with positive attitudes toward computers in education and constructivist beliefs showed more interest in using digital technology while teaching. Because of the mix of factors contributing to the intent to use technology, the researchers posited a need for more research regarding the CSE of digital natives and whether it does constitute the bulk of what drives their attitudes and behaviors. This call to research, in alignment with generational researchers, suggests the connection between digital native status and CSE may be interrelated with regard to the attitude and behaviors of individuals, but more empirical research is warranted. However, despite the considerable attention given to digital natives, few researchers have investigated the characteristics of this group and others argue that the term “digital native” no longer accurately reflects today’s student (Bullen & Morgan, 2011; Gallardo-Echenique et al., 2015; Yong & Gates, 2014).

According to Bullen and Morgan (2011) students today are on a continuum of technological access irrespective of age. Additionally, skill, ease of use, and comfort level also vary. In the scholarship, age is the most cited criteria for defining digital natives (Teo, 2016). However, an issue with age is that teachers are often older than their students. If digital natives are defined by their experience and exposure to digital technology, then they should be more proficient than their teachers. However, this is not the case (Bullen and Morgan, 2011). Just because a student was born after 1980 does not mean that they will be competent in digital learning. Likewise, just because someone is born before 1980 does not mean that they cannot speak this digital language. Gallardo-Echenique et al. (2015) showed that there is no fundamental difference between digital natives and immigrants and that the traditional characteristics that define digital natives can only be found in a minorty of students.

Being a digital native has more to do with experience and access and less to do with age (Gallardo-Echenique et al., 2015). Be that as it may, the technology surrounding digital natives/learners affects the way they think, behave, and interact with the world. The modern classroom has adapted by using more team-based, collaborative learning, and game-based learning. In turn, this has had a profound impact on pedogagy, and school policy and planning.

Summary of the Chapter

Online education has become an important mode of delivery for institutions of higher education. It requires considerable discipline relative to traditional F2F courses because instruction takes place away from the institution and not in presence of an instructor. In higher education, self-efficacy as a motivation construct can be defined as the confidence one has to be successful in academic activities (Hodges, 2008). The principles of self-efficacy are context specific and must be considered as circumstances change. For example, the shift from traditional F2F courses to online learning may affect the student's self-efficacy. The social cognitive work of Bandura (1977, 1997) proves crucial to understanding the principles of self-efficacy.

Online learning requires students to be motivated and confident in both their academic and computer abilities. Understanding this is crucial to measuring student success. Measuring student success with respect to self-efficacy requires understanding the role of digital literacy, and student attitude, both of which are important factors for measuring success in online courses. Research shows that positive student attitude and student satisfaction results in higher student self-efficacy (Prior et al., 2016).

An examination of the literature shows that the unifying characteristics of digital learners is their innate comfort and confidence using technology (Ripley, 2013). This confidence, known as CSE, has been the subject of studies with regard to knowledge sharing, research and learning (Gallardo-Echenique et al., 2015), organizational culture (So et al., 2012), generational expectations, anxiety (Bellini et al., 2016), personality, gender (Jan, 2015), and culture (Shao et al., 2015). Computer self-efficacy research is rooted in the general theory of self-efficacy, which postulates an individual's belief in his or her ability to achieve can directly impact his or her achievement (Bandura, 1986). As a result, digital learners should have higher levels of CSE.

In the context of online learning, self-efficacy is especially important. Online learning is self-directed and requires increased discipline on the part of the student. Because self-efficacy is concerned with a person's confidence in her/his abilities to complete certain tasks and reach specific goals, it has huge implications for online educators. Self-efficacy studies are vital because they are often seen as a predictor of student success and academic performance. While there is no doubt that there are differences in the self-efficacy between males and females, the data is inconsistent. Understanding the role that self-efficacy plays in online learning is vital for understanding how best to serve our students.

Chapter 3: Methodology

Introduction

In today's classroom, computer-based technology is a vital component for any student. Computer-based technology is so prevalent that most traditional F2F classes have some form of online component (Broadbent & Poon, 2015). In fact, online learning and the number of students enrolling in online courses is increasing every semester (Means et al., 2013). Institutions of higher education have responded to increased enrollment by increasing the number of online courses. In California, an initiative is underway to create the California Online Community College. However, despite increasing enrollment over the past several years, online learning continues to have lower retention and completion rates (Travers, 2016). In fact, while online education is gaining in popularity, academic institutions are struggling with the high rates of attrition associated with online learning (Lee, 2015). As a result, studies examining the role of self-efficacy in general and CSE in particular has received growing attention (Dang et al., 2016; Lee, 2015; Prior et al., 2016). Understanding the role of CSE in completion rates could provide educators an insight into maintaining student enrollments.

Self-efficacy is a valid measure for predicting grade point averages and overall academic success (Thangarasu & DePaul, 2014). Online learning plays a significant role in higher education and self-efficacy has become a useful tool for examining student confidence and successful completion of the course (Vayre & Vonthron, 2017; Voyer & Voyer, 2014). As a result, factors such as student success and completion rates are important considerations when considering the success of online learning.

Research on computer and self-efficacy mainly refers to students' confidence in their ability of using computers and other related technology (Cassidy & Eachus, 2002; Compeau &

Higgins, 1995; Howard, 2014). Being successful in online education requires the student to be effective with online technology. Online learning requires the student to have both academic and CSE (Jan, 2015). Research shows that prior computer training plays a significant role in helping to distinguish between students who completed online distance education courses and those who did not (Jan, 2015). Students with higher levels of CSE believe in the value of computer learning and are more engaged in the learning process. (Pellas, 2014). Furthermore, studies show that students with increased levels of CSE tend to spend more time using online learning technology and those students were more easily engaged in the learning process (Vayre & Vonthron, 2017).

An examination of the literature shows that the unifying characteristics of digital natives is their innate comfort and confidence using technology (Ripley, 2013). This confidence, known as CSE, has been the subject of studies with regard to knowledge sharing, research, and learning (Gallardo-Echenique et al., 2015); organizational culture (So et al., 2012); generational expectation and anxiety (Bellini et al., 2016); personality and gender (Jan, 2015); and culture (Shao et al., 2015). Computer self-efficacy research is rooted in the general theory of self-efficacy, which postulates an individual's belief in his or her ability to achieve can directly impact his or her achievement (Bandura, 1986). As a result, digital natives should have higher levels of CSE.

The purpose of this study is to examine if there is a relationship between higher levels of CSE and completion rates among online California community college students. For the purpose of this research, course completion will be defined as those students who pass their online course with a C or better. Additionally, the researcher used a 12-item CUSE Scale. This scale was administered in the form of a questionnaire and was used to determine the student's level of

CSE. At the end of the term, the student's level of CSE was compared to whether or not they completed the course.

Statement of the problem

The purpose of this study was to examine if CSE influences completion of online courses in California community colleges. In this quantitative correlational study CUSE scale and final course grades were the data sources. The CSE scores of the students were analyzed and compared to their final course grades.

Research Question

The following research question guided this study:

RQ1. To what extent is there a relationship between higher levels of computer self-efficacy and the completion of online courses between in California community colleges?

Hypothesis

H_o: There is no relationship between higher levels of computer self-efficacy and completion of online courses in California community colleges.

H_a: There is a positive relationship between higher levels of computer self-efficacy and the completion of online courses in California community colleges.

Research Design

A quantitative correlational design was used for this study to examine to what extent, if any, does a relationship exist between CSE and course completion. Adams and Lawrence (2015) describe a correlation design as type of research that hypothesizes the relationship between variables. Additionally, correlational research requires a data set to determine the existence of a relationship between two or more quantifiable variables and the extent of that relationship. When a selected range of scores in one variable are cognates to scores on other variables, there is evidence of a relationship. As a result, correlational relationships have a vital role in making predictions.

The researcher determined that a correlational design was the appropriate method to implement for this investigation. Correlational research designs address whether a significant difference in the relationship of a sample exists purely by chance or if the relationship is accurately reflected in the population (Adams & Lawrence, 2015). One advantage of the correlation design is that it focuses on the relationships that remain constant among variables (Adams & Lawrence, 2015). As a result, this study will use a 12-item CUSE Scale (Howard, 2014) . Originally developed by Compeau and Higgins (1995), the Cassidy and Eachus (2002) CUSE scale focuses on the measurement of CSE in student computer users and its significance to learning in higher education. The process of hypothesis testing will allow for insightful considerations to find this consistent relationship and test to see if a significant difference appears by pure chance (Adams & Lawrence, 2015).

To be statistically significant the research must achieve a correlation coefficient distinctive from zero or irrelative (Gay, Mills, & Airasian, 2012; Thangarasu & DePaul, 2014). Therefore, a correlation coefficient lower than +.35 or -.35 suggests a relationship with little or no association between variables. A correlation coefficient between +/-.35 or +/-.65 suggests a moderate relationship with a high relationship existing between variables with a correlation coefficient of +/-.65. However, a correlation coefficient of plus or minus .60 or .70 are acceptable for making prediction where groups are involved ("Pearson's product-moment correlation," 2018). Moderate to high significance will lead to generalizations and will add to the body of existing research on CSE, online course completion rates and gender differences. High significance will lead to predictions about CSE and online course completion rates as well the differences between genders with respect to CSE. A main disadvantage of the correlation design is that correlation does not determine causality. Therefore, further research will be needed to determine if CSE plays a role in online completion rates and if gender differences exists.

Target Population, Sampling Method (power) and Related Procedures

The California community college System is the nation's largest system of higher education totaling 114 colleges. According to the CCC ("Annual/term student count report," 2018) as of Spring 2018, there were 1,473,863 students enrolled. This extremely diverse system includes 44.7% Hispanic, 26.38% white non-Hispanic, 11.44% Asian, 5.76% African-American, 3.9% multi-ethnic, 0.43% American Indian/Alaskan Native, 0.40% Pacific Islander, and 2.76% Filipino. Of the 1.4 million students 56% are female and 44% are male with 22% being unknown. The target population for this study will come from a community college in California.

Data from the CCC (2018) shows that the college served 8,941 students in spring 2018. Demographic information for this college shows 37.69% white non-Hispanic, 22.96% Hispanic, 15.46% Asian, 14.58% unknown, 4.90% multi-ethnic, 2.02% Filipino, 1.99% African-American, 0.20% American Indian/Alaskan Native, and 0.19% Pacific Islander, and. Demographic information shows that females make up 56.47% of the student population with males at 42.09% and 1.44% being unknown.

During the term, 1,443 students were enrolled in online courses offered by the Social Sciences Division at the college. The retention rate for that semester was 82.47% and an overall success rate of 65.07%. The success rate for the identified age groups are as follows: 1–17, 89.66% for ages 1–17, 64.30% for ages 18–19, 65.37% for ages 20–24, 62.15% for ages 25–29, 54.39% for ages 30–34, 75.68% for ages 35–39, 58.54% for ages 40–49, and 85.71% for all ages above 50. Interestingly, the age ranges with the highest success rates are ages 1–17 (89.66%) and +50 (85.71; ("Annual/term student count report," 2018).

To determine the sample size, a power analysis for a-priori sample size for *t* tests measuring differences between two dependent means (matching pairs) will be calculated using G*Power 3.1 statistical test (Faul, Erdfelder, Lang, & Buhner, 2007). For the test to be statistically significant, the researcher used a correlation of 0.09 $r^2 < .25$ for a medium effect. Therefore, a correlation of (r^2) of 0.2 was used with the G*Power 3.1 software. This resulted in an equivalent effect size of $|\rho|$ of 0.4472136, an error probability of 0.05, and a Power (1β error probability) of 0.95. The resulting sample size was 45 students and an actual power of 0.9511155.

In this study, two semesters were used: Spring and Summer 2019. It was necessary to give the CUSE survey during the first two weeks of the semester in an effort to reduce bias. Research shows that with respect to online courses, student gain more confidence in their ability as the semester progresses (Jan, 2015). However, institutional approval to collect data from community college used in this study was not given until after the Spring 2019 semester began. Therefore, late-start courses were chosen. These late-start courses were six weeks long and ran from April 4 through May 24, 2019. Only one instructor volunteered their courses (sociology). This resulted in a convenience sampling being used to choose the online courses represented in this research.

Instrumentation

The CUSE is a widely used measure for examining a student's CSE (Howard, 2014). Compeau and Higgins (1995) tested several hypotheses related to the computer use and social cognitive theory. They showed that people who enjoyed using computers experiences less computer anxiety. Since then, the CUSE has been modified by Cassidy and Eachus (2002) and Howard (2014) to account for changes in computer nomenclature and technology. Cassidy and Eachus (2002) expanded on Compeau and Higgins (1995) model. They created a 30-item CUSE scale which was designed to measure general CSE in adult students (Jan, 2015) and focused on expectations, human-computer interface, and proficiency on software applications.

However, Howard (2014) noted that existing methods of CSE were deficient. He sought to develop a more modern instrument for today's CSE research. Howard identified multiple issues with existing CSE instruments prominently falling within three themes. First, some of the items in popular CSE instruments could be influenced by factors outside the realm of CSE, such as reading abilities, learning capacity, anxiety, or the context of computer use. Second, some elements in popular CSE instruments tend to measure technical skills rather than self-efficacy. As the definition of CSE addresses belief over ability, these items are misaligned. Finally, Howard notes that some items used to measure CSE are irrelevance and outdated. Instruments included items regarding obsolete technology such as floppy disks, mainframe systems, and DOS-based computer packages (p. 678).

In response to these issues, Howard (2014) developed a 12-item instrument through the process of exploratory and confirmatory factor analysis. The instrument was also tested for criterion validity against a well-known and popular existing CSE scale. The new instrument was reported to have "superb psychometric properties . . . excellent internal consistency . . . and seem[ed] to be a satisfactory tool for future research" (p. 680). This instrument provides an opportunity to investigate CSE in a modern context to continue to answer calls for future research with regard to CSE mediators, moderators, predictors, and outcomes. As a result, this scale will be employed in this research design. For this study, the researcher used the CUSE scale developed by Howard (2014). This scale consisted of 12 questions developed by Howard (2014). The questions will use a 6-point Likert scale.

Data Collection

Prior to data collection, permission was required from the Social Science division at the community college where the research was carried out as well as from the Institute Review Board (IRB) at Concordia University. Permission was given from the community college in January 2019. This allowed for the completion of the IRB process and IRB permission was given in March 2019.

Between January and March 2019 the principal investigator emailed the online social science faculty seeking volunteers for this research. Only one sociology instructor gave their consent for data to be collected using the CUSE survey. The instructor of the online course sent an email to the students informing them of the survey. The email, provided by the researcher, explained the nature and scope of the survey and that the survey was voluntary. In addition, the email explained that the college had approved the study and that students can provide their informed consent to participate in the survey. Informed consent forms were sent as an attachment in the initial email.

The CUSE survey was conducted through Qualtrics, a web-based program that is used to create surveys and polls, distribute them to users, and generate reports. The survey was sent at the beginning the Spring 2019 late-start semester (March 2019). The survey was conducted during the first two weeks of classes to gauge the student's level of CSE at the beginning of the term. At the conclusion of the spring 2019 term, the online course instructor provided the researcher with a list of students who participated and successfully completed the course with their final course grades. The CUSE scores which were generated from the survey was then compared to the student's final course grade.

Data Analysis Procedures

The data collected through Qualtrics was used to determine the students' level of CSE. These scores were derived from 12 questions using a 6-point Likert scale categorized from strongly disagree to strongly agree. From these 12 questions, the highest possible score is 72 (100%). To obtain the student's CSE score, the Likert number for all questions were added. Student's CSE score was determined by adding the Likert number from each of the 12 questions. The highest possible score was 72. Scores with values over 60 indicated students with higher levels of CSE. These values were then entered into SPSS (a computer program that performs statistical calculation) using Spearman's ranked order correlation (Spearman's $r_{s)}$. Spearman's r_s is a statistical method used to measure the strength and direction of the association between two continuous variables, two ordinal variables, or one ordinal and one continuous variable ("Spearman's correlation," 2018).

Likert data are ordinal and should be analyzed with non-parametric statistics because the distances between the response options are not consistent. Spearman's r_s determines the degree to which a relationship is monotonic. That is, there is a monotonic association between two ordinal variables. Statistical guidelines for approximate strength of correlation for Spearman's r_s are similar to that of Pearson's. Values between .00–.19 are considered "very weak," .20–.39 "weak," .40–.59 "moderate," .60–.79 "strong," and .80–1.0 "very strong" (Adams & Lawrence, 2015).

Limitations of the Research Design

This quantitative correlational study may find that a relationship does exist between CSE and course completion rates. However, this association does not necessarily mean that a casual relationship exists between CSE and course completion. As a result, further investigations will need to be performed. The instrument used to collect data in this study was a survey, which relies on participant honesty Adams and Lawrence (2015) report that participant honesty can be a problem with surveys in higher education. Also, because there is no scientific measure for identifying higher levels of CSE, it is incumbent upon every researcher to carefully delineate what higher levels of CSE mean and articulate that. Finally, this study cannot be seen as representative of the entire California community college System (CCC). The CCC is quite diverse with large metropolitan community colleges and small rural community colleges. This study is only focusing on one community college in California.

Ethical Issues in the Study

The researcher is affiliated with the community colleges for the study. As a result, some of the participants in this survey might recognize the principal researcher. This knowledge could have biased their responses.

Approval for this research was granted in March 2019 by Concordia University Institutional Review Board (IRB). With this approval, permission was granted by the Dean of Social Sciences from the community college where the research was conducted. To minimize any conflict of interest, the researcher had no contact with the students who participated in the survey. The instructor of the courses surveyed emailed all students with an introduction letter, written by the principle researcher, to solicit volunteers to participate in the study. Data was collected and stored through Qualtrics. The information was encrypted and cannot be accessed.

All other information such as students' names and grades has been retained and stored by the instructor of the classes surveyed.

Chapter 3 Summary

Online education has become an important mode of education for institutions of higher education (Jan, 2015). However, online learning requires considerable discipline relative to traditional F2F courses because instruction takes place away from the institution and not in presence of an instructor (Vayre & Vonthron, 2017). As a result, online learning requires that students are motivated and confident in both their academic and computer abilities. Understanding this is crucial to measuring student success (Pellas, 2014).

The intention of this study was to examine the relationship between CSE and completion rates in online courses in the California community college system. The purpose of the research was to examine if a relationship exists between higher levels of CSE and course completion rates in online courses. The intent is to provide some clarity regarding the role of CSE in completion rate and to examine if this effects digital learners.

A quantitative correlational research design was used for this study. Correlational research designs are used to examine whether a significant difference in the relationship of a sample exists purely by chance or if the relationship is accurately reflected in the population. To test this a 12-item CUSE was used to measure student's confidence in their ability to solve computer related problems. Because institutional approval was granted after the beginning of the spring 2019 semester, late-start courses was used. This dramatically reduced the number of courses being offered, so a judgement sample was used.

Presently, the literature is inconsistent regarding the relationship between CSE and digital learners (Aktürk, 2014; Jan, 2015; Samruayruen, Enriquez, Natakuatoong, & Samruayruen, 2013). Additionally, the researcher hopes to bring attention to the importance of CSE in online learning and to examine if differences exist with digital learners. It is hoped that this research will add to the growing body of literature for role of CSE in general and the role of CSE for digital natives in particular.

Chapter 4: Data Analysis and Results

Introduction

This study examined if higher levels of CSE contributes to online course completion among online California community college students. A quantitative correlational design was used to examine the research question: To what extent is there a relationship between higher levels of CSE and the completion of online courses in California community colleges? The purpose of this chapter is to provide insight on the data gathered and discuss conclusions regarding the analysis and results of the study. Data for this study will consist of a CUSE score and final course grades. The CUSE score was calculated from surveys administered to online students in the Social Sciences Department at a California community college.

The data used in this study was gathered using a CUSE survey administered through Qualtrics, an online survey platform. The survey consisted of 12 questions with a six-point Likert response scale. Additionally, the survey consisted of three questions regarding perceived use of computers (see Appendix A). The CUSE scores were derived from 12 questions using a six-point Likert scale from strongly disagree to strongly agree. From these 12 questions, the highest possible score is 72 (100%). To obtain the student's CSE score, the Likert numbers for all questions were added. Student's CSE score was determined by adding their score for each question with the highest possible score 72. Scores with values over 60 will indicate students with higher levels of CSE, while scores under 60 will indicate students with low levels of CSE (Howard, 2014). Once these scores were calculated, they were then compared to their final course grade. The values were then entered into SPSS (a computer program that performs statistical calculation) using Spearman's ranked order correlation (Spearman's r_s). Spearman's r_s is a statistical method used to measure the strength and direction of the association between two continuous variables, two ordinal variables, or one ordinal and one continuous variable ("Spearman's correlation," 2018).

Data were gathered from online courses in sociology at a community college in California. Online students were recruited from late-start and summer courses during the Spring/Summer 2019 semester. The course instructor disseminated an introduction email from the principle investigator. This email provided an overview of the study outlining the purpose of the study explaining the survey along with the link to the Qualtric survey (see Appendix B). The student consent form was sent as an attachment (see Appendix C).

Description of the Sample

In this study, two semesters were used: Spring and Summer 2019. It was necessary to give the CUSE survey during the first two weeks of the semester in an effort to reduce bias. Research shows that with respect to online courses, student gain more confidence in their ability as the semester progresses (Jan, 2015). However, institutional approval to collect data from community college used in this study was not given until after the Spring 2019 semester began. As a result, late start courses were chosen. These late-start courses were six weeks long and ran from April 4 through May 24, 2019. A convenience sampling was used to choose the online courses represented in this research.

The community college used in this study offered 20 late-start and 25 summer sections. An email was sent to all instructors teaching these sections seeking permission to collect data. One sociology instructor gave permission to collect data during late-start spring and summer courses. The three courses used in this study were SOCI 002: Social Problems, SOCI 020: Sociology of Race and Ethnicity, and SOCI 028: Sociology of Gender. Table 1 lists each course used in this study by semester.

Table 1

Courses by Term

Course name	Late-Start Spring 2019	Summer 2019
SOCI 002	1 section	2 sections
SOCI 020	1 section	1 section
SOCI 028	1 section	none

One hundred ninety-four students were enrolled in these six sections resulting in 133 surveys. Of the 133 surveys collected, 122 were used. The 11 surveys that were not used consisted of missing information (four students), duplicates (four students), or the student dropped the course (three students). Overall, 54% of the respondents were female, 41% were male, and 5% declined to state. Table 2 provides a break down by section with 66 female respondents, 50 male respondents, five declining to state their gender, and one student who did not answer the question.

Table 2

Demographic data for the Participants

Section	*N* = 59	Percentage Breakdown
SOCI 002	59	
Gender		
Female	28	47.5%
Male	28	47.5%
Decline to State	2	3%
Did not answer	1	2%
SOCI 020	41	
Gender		
Female	21	51%
Male	17	42%
Decline to State	3	7%
SOCI 028	22	
Gender		
Female	17	77%
Male	5	23%
Decline to State	0	

Summary of the Results

The data analysis of this study fit the applied research approach for a quantitative study. As such, a quantitative correlational design was the appropriate method to implement for this investigation. Correlational research designs address whether a significant difference in the relationship of a sample exists purely by chance or if the relationship is accurately reflected in the population (Adams & Lawrence, 2015). One advantage of the correlation design is that it focuses on the relationships that remain constant among variables (Adams & Lawrence, 2015). This study used a 12-item CUSE Scale developed by Howard (2014) and has been shown to have considerable reliability and validity (Loar, 2018). The process of hypothesis testing allowed for insightful considerations to find this consistent relationship and test to see if a significant difference appears by pure chance (Adams & Lawrence, 2015). The following research question was investigated for this study:

RQ1. To what extent is there a relationship between higher levels of computer self-efficacy and the completion of online courses in California community colleges? The hypotheses for this study are as follows:

H_o: There is no relationship between higher levels of computer self-efficacy and completion of online courses in California community colleges.

H_a: There is a positive relationship between higher levels of computer self-efficacy and the completion of online courses in California community colleges.

Testing these hypotheses will be done using a CUSE scale.

The CUSE scale was originally developed by Compeau and Higgins (1995) and asked participants how competent they felt they were in their ability to use standard and new work-related programs. However, this scale focused on hypothetical work-related programs. As a result, many researchers argued that this scale was a measure of learning self-efficacy and not CSE. Other CUSE scales have been used with various degrees of success (Howard, 2014). For example, Cassidy and Eachus (2002) CUSE scale focused on the measurement of CSE in student computer users and its significance to learning in higher education. While their scale was an improvement over earlier versions, it did have its flaws, most notably in the outdated language and psychometric properties (Howard, 2014). Howard's CUSE scale has been demonstrated to work with both students and non-students to have excellent internal consistency and validity, making it a satisfactory tool for CUSE research (Correia, Compeau, & Thather, 2016; Howard & Jayne, 2015).

Detailed Analysis

The research question that guided this study was: To what extent is there a relationship between higher levels of computer self-efficacy and the completion of online courses in California community colleges? To test this research question the following null hypothesis was used:

H_o: There is no relationship between higher levels of computer self-efficacy and completion of online courses in California community colleges.

Alternatively, we must assume:

H_a: There is a positive relationship between higher levels of computer self-efficacy and the completion of online courses in California community colleges.

To test the above hypothesis a CUSE questionnaire was distributed to six online sociology courses at a California community college. The CUSE questionnaire consisted of a CUSE survey and three open-ended questions. The CUSE survey asked participants 12 questions regarding their ability to solve computer related problems. These questions reflect computer related problems frequented in online courses. The respondents were asked to indicate the strength of their agreement or disagreement of the statements using a 6-point Likert scale ranging from "strongly disagree" to "strongly agree" (see Appendix C). Table 3 gives the percentages of responses for each Likert point.

Likert score data. Question 1 asked: I can always manage to solve difficult computer problems if I try hard enough. Of the 122 responses, two students responded with 1 or "strongly disagree," eight students responded with 2 on the Likert scale, 21 students responded with 3, 40 responded with 4, 28 responded with 5, and 23 responded with 6 or "Strongly agree."

Question 2 asked: If my computer is "acting-up," I can find a way to get what I want. Of the 122 responses, two students responded with 1 or "strongly disagree," 12 students responded with 2 on the Likert scale, 25 students responded with 3, 32 responded with 4, 26 responded with 5, and 25 responded with 6 or "Strongly agree."

Question 3 asked: It is easy for me to accomplish my computer goals. Of the 122 responses, two students responded with 1 or "strongly disagree," five students responded with 2 on the Likert scale, 14 students responded with 3, 33 responded with 4, 35 responded with 5, and 33 responded with 6 or "Strongly agree."

Question 4 asked: I am confident that I could deal efficiently with unexpected computer events. Of the 122 responses, four students responded with 1 or "strongly disagree," 14 students responded with 2 on the Likert scale, 33 students responded with 3, 36 responded with 4, 18 students responded with 5, and 17 students responded with 6 or "Strongly agree."

Question 5 asked: I can solve most computer programs if I invest the necessary effort. Of the 121 responses, six students responded with 1 or "strongly disagree," nine students responded with 2 on the Likert scale, 25 students responded with 3, 28 responded with 4, 27 students responded with 5, and 26 students responded with 6 or "Strongly agree." One student left this question blank.

Question 6 asked: I can remain calm when facing computer difficulties because I can rely on my abilities. Of the 122 responses, four students responded with 1 or "strongly disagree," 17 students responded with 2 on the Likert scale, 27 students responded with 3, 25 responded with 4, 28 students responded with 5, and 21 students responded with 6 or "Strongly agree."

Question 7 asked: When I am confronted with a computer problem, I can usually find several solutions. Of the 122 responses, three students responded with 1 or "strongly disagree," 24 students responded with 2 on the Likert scale, 18 students responded with 3, 28 responded with 4, 28 students responded with 5, and 21 students responded with 6 or "Strongly agree."

Question 8 asked: I can usually handle whatever computer problem comes my way. Of the 122 responses, seven students responded with 1 or "strongly disagree," 14 students responded with 2 on the Likert scale, 28 students responded with 3, 32 responded with 4, 21 students responded with 5, and 20 students responded with 6 or "Strongly agree."

Question 9 asked: Failing to do something on the computer makes me try harder. Of the 121 responses, eight students responded with 1 or "strongly disagree," 17 students responded with 2 on the Likert scale, 18 students responded with 3, 28 responded with 4, 28 students responded with 5, and 22 students responded with 6 or "Strongly agree." One student left this question blank.

Question 10 asked: I am a self-reliant person when it comes to doing things on a computer. Of the 122 responses, four students responded with 1 or "strongly disagree," eleven students responded with 2 on the Likert scale, 20 students responded with 3, 24 responded with 4, 36 students responded with 5, and 27 students responded with 6 or "Strongly agree."

Question 11 asked: There are few things that I cannot do on a computer. Of the 122 responses, five students responded with 1 or “strongly disagree,” 17 students responded with 2 on the Likert scale, 15 students responded with 3, 22 responded with 4, 39 students responded with 5, and 24 students responded with 6 or “Strongly agree.”

Question 12 asked: I can persist and complete most any computer-related task. Of the 122 responses, four students responded with 1 or “strongly disagree,” eight students responded with 2 on the Likert scale, 13 students responded with 3, 31 responded with 4, 38 students responded with 5, and 28 students responded with 6 or “Strongly agree.” Table 3 provides the percentages for each Likert scores.

Table 3

Percentages of Responses for Computer User Self-efficacy Scale Survey

Question #	Strongly disagree 1	2	3	4	5	Strongly agree 6	*N*
1. I can always manage to solve difficult computer problems if I try hard enough.	1.64%	6.56%	17.21%	32.79%	22.95%	18.85%	122
2. If my computer is "acting-up," I can find a way to get what I want.	1.64%	9.84%	20.49%	26.23%	21.31%	18.85%	122
3. It is easy for me to accomplish my computer goals.	1.64%	4.10%	11.48%	27.05%	28.69%	27.05%	122
4. I am confident that I could deal efficiently with unexpected computer events.	3.28%	11.48%	27.05%	29.51%	14.75%	13.93%	122
5. I can solve most computer programs if I invest the necessary effort.	4.96%	7.44%	20.66%	23.14%	22.31%	21.49%	121
6. I can remain calm when facing computer difficulties because I can rely on my abilities.	3.28%	13.93%	22.13%	20.49%	22.95%	17.21%	122
7. When I am confronted with a computer problem, I can usually find several solutions.	2.46%	19.67%	14.75%	22.95%	22.95%	17.21%	122
8. I can usually handle whatever computer problem comes my way.	5.74%	11.48%	22.95%	26.23%	17.21%	16.39%	122
9. Failing to do something on the computer makes me try harder.	6.61%	14.05%	14.88%	23.14%	23.14%	18.18%	121
10. I am a self-reliant person when it comes to doing things on a computer.	3.28%	9.02%	16.39%	19.67%	29.51%	22.13%	122

Question #	Strongly disagree 1	2	3	4	5	Strongly agree 6	*N*
11. There are few things that I cannot do on a computer.	4.10%	13.93%	12.30%	18.03%	31.97%	19.67%	122
12. I can persist and complete most any computer-related task.	3.28%	6.56%	10.66%	25.41%	31.15%	22.95%	122

Using the Likert scale data presented above, the mean and standard deviation were also calculated. This data show that most responses were between three and five. Table 4 provides the descriptive data for each question.

Table 4

Mean and SD for Computer User Self-efficacy Scale Survey

Question #	*N*	Mean	*SD*
1. I can always manage to solve difficult computer problems if I try hard enough.	122	4.25	1.23
2. If my computer is "acting-up," I can find a way to get what I want.	122	4.17	1.32
3. It is easy for me to accomplish my computer goals.	122	4.58	1.21
4. I am confident that I could deal efficiently with unexpected computer events.	122	3.83	1.30
5. I can solve most computer programs if I invest the necessary effort.	121	4.15	1.42
6. I can remain calm when facing computer difficulties because I can rely on my abilities.	122	3.98	1.41
7. When I am confronted with a computer problem, I can usually find several solutions.	122	3.96	1.44
8. I can usually handle whatever computer problem comes my way.	122	3.87	1.42
9. Failing to do something on the computer makes me try harder.	121	3.97	1.50
10. I am a self-reliant person when it comes to doing things on a computer.	122	4.30	1.38
11. There are few things that I cannot do on a computer.	122	4.19	1.46
12. I can persist and complete most any computer-related task.	122	4.43	1.31

CUSE score data. The CUSE score was calculated by adding the score for each question. The maximum score attainable was 72. It was determined that scores between 60–72 would be consistent with high levels of CSE, while scores below 60 would be consistent with low levels of CSE (Howard, 2014). These scores were then compared to the student's final course grade. The section below will examine the CUSE scores for each section used in this study.

Late-Start SOCI 002. Twenty students from this section participated in the survey. Of the 20 students, 16 had scores consistent with low CSE. The average CUSE score for this section was 49.45. In this section, 80% of the students reported low CUSE scores with 20% reporting high levels of CSE. The minimum CUSE score was 24, while the maximum score was 72. The descriptive data for this section is presented in table 5.

Late-Start SOCI 020. Sixteen students from this section participated in the CUSE survey. Of the 16 students 14 had scores consistent with low CSE. The average CUSE score for this section was 48.31. In this section, 87.5% of the students reported low CUSE scores with 12.5% reporting high levels of CSE. The minimum CUSE score was 29, while the maximum score was 72. The descriptive data for this section is presented in table 5

Late-Start SOCI 028. Twenty-two students from this section participated in the CUSE survey. Of the 22 students 14 had scores consistent with low CSE. The average CUSE score for this section was 53.05. In this section, 63.6% of the students reported low CUSE scores with 36.4% reporting high levels of CSE. The minimum CUSE score was 36, while the maximum score was 72. The descriptive data for this section is presented in table 5.

Summer SOCI 002-001. Fourteen students from this section participated in the CUSE survey. Of the 14 students, 13 had scores consistent with low CSE. The average CUSE score for this section was 44.71. In this section, 85.7% of the students reported low CUSE scores with 14.3 reporting high levels of CSE. The minimum CUSE score was 27, while the maximum was 62. The descriptive data for this section is presented in table 5.

Summer SOCI 002-002. Twenty-five students from this section participated in the CUSE survey. Of the 25 students, 18 had scores consistent with low CSE. The average CUSE score for this section was 49.88. In this section, 68% of the students reported low CUSE scores with 32% reporting high levels of CSE. The minimum CUSE score was 15, while the maximum was 72. The descriptive data for this section is presented in table 5.

Summer SOCI 020. Twenty-five students from this section participated in the CUSE survey. Of the 25 students, 21 had scores consistent with low CSE. The average CUSE score for this section was 49.68. In this section, 80% of the students reported low CUSE scores with 20% reporting high levels of CSE. The minimum CUSE score was 16, while the maximum was 72. The descriptive data for this section is presented in table 5.

Table 5

Computer User Self-efficacy Score

Section	*N*	*M* (*SD*)	95% CI
Late-Start Spring SOCI 002	20	49.45 (14.39)	42.72 to 56.18
Late-Start Spring SOCI 020	16	48.31 (12.4)	41.70 to 54.92
Late-Start Spring SOCI 020	22	53.05 (10.76)	48.27 to 57.82
Summer SOCI 002-001	14	44.71 (11.16)	38.27 to 51.16
Summer SOCI 002-002	25	49.88 (15.75)	43.38 to 56.38
Summer SOCI 020	25	49.68 (13.71)	44.02 to 53.34

Overall, 122 surveys were completed. Of these completed surveys 93 had CUSE scores consistent with low CSE, while 29 had CUSE scores consistent with high levels of CSE. This means that 76% of all students surveyed had low CSE, while only 24% recorded high levels of CSE. The descriptive data for all completed surveys is presented in table 6.

Table 6

Computer User Self-efficacy Score

	N	*M (SD)*	95% CI
Low CUSE (0–59)	93	44.19 (10.27)	42.08 to 46.31
High CUSE (60–72)	29	66.69 (4.17)	65.10 to 68.27

Additionally, CUSE scores were tabulated relative to gender. On average, females recorded lower levels of CSE than did males. The descriptive data by gender is presented in table 7.

Table 7

CUSE scores by gender

	N	*M (SD)*	95% CI
Female	66	47.11 (11.73)	44.22 to 49.99
Male	50	52.26 (14.87)	48.03 to 56.49
Decline to state	5	53.67 (12.08)	40.99 to 66.34

Questionnaire data. In addition to this CUSE scale, three questions were asked: What type of technology do you normally use? What type of computer problems do you normally experience? With respect to computers, what do you feel your experience level is?

With respect to the first question, “What type of technology do you normally use?” 100% of the respondents listed computers and cell/mobile phones as the type of technology they normally use. Other forms of technology used included, gaming systems: 12%, internet: 12%, television: 11%, printer: 3%, digital cameras: 2%, digital recorders: 2%, 3D printing: 2%, and car, washing machine, dryer, dishwasher, microwave, and oven were < 1%.

Question two asked, “What type of computer problems do you normally experience?” With regards to this question, 120 students responded and, 2 left this question blank. In all 162 “computer problems” were listed. Most students reported that their main computer problem was slow computers, slow internet or both. In fact, of the 120 responses, “slow” or “slowing computer” was mentioned 25% of the time. With regards to the internet, “slow,” “poor,” or “connectivity” issues was mentioned 23% of the time. The remaining computer related problems recorded by the students are listed in ranked order and provided in Table 8.

Table 8

Computer related problems

	N = 120
Slow computer	41
Slow internet	38
Programs:	15
Excel	5
Office	1
Other	9
No computer problems	10
Pop-ups	8
Connecting printer	7
Up/downloading	6
Battery	5
Bugs/viruses	5
Bad communication	5
Computer heating up	5
Opening documents	5
Installing updates	4
“glitches”	4
Spam/spyware	3
Computer shutting down.	2
Setting up new devices	2
Connection projector	1
Flashback	1
Storage	1

The final question asked, “What is your experience level with computers?” For this question, there were 118 responses with four students not responding. Of the 118 responses, 9 students, or 7.6%, listed their experience level with computes as none, nearly none, not much, or not too well. The average CUSE score for these students was 38.44 which is consistent with a low CSE score. Sixty-eight students, or 57.6%, classified themselves as moderate or intermediate with respect to their experience level with computers. This number includes students who listed themselves as average, medium, competent, casual user, very basic, simple programming, or rated themselves on an ordinal scale of either 6, 7, or 8. It should be noted that these students had an average CUSE score of 47.12 which is consistent with a low CUSE score. Forty-one students, or 34.7%, viewed their computer experience as expert, advanced, perfect, genius, high, experienced, very proficient, or listed themselves as 9 or 10 on an ordinal scale. Their average CUSE score was 56.44. While this number is still consistent with a low CUSE score, it is higher than the other groups. The four students who did not answer the questions had an average CUSE score of 45. Again, this number is consistent with a low CUSE score.

Course grades. At the end of each semester, the students' CUSE score were compared to their final course grade. For the three Spring 2019 late-start courses, 58 students completed the CUSE survey. Of the 58 students 56 successfully passed their courses and two did not. Final course grades for each late-start section are listed in Table 9.

Table 9

Late-Start Final Course Grades: Spring 2019

Section	A	B	C	D	F	*N*
SOCI 002	13	6	1	0	0	20
SOCI 020	8	4	2	1	1	16
SOCI 028	17	2	3	0	0	22

The combined sections above carry a 96.5% pass rate. SOCI 002 had a 100% pass rate with the class average being 92.95/A. SOCI 020 had a pass rate of 87.5%. However, two students did not pass this course (see Table 8). The class average for this course was 85.88/B. SOCI 028 had a 100% pass rate with the class average being 93.41/A.

For the three Summer 2019 sections, 64 students completed the CUSE survey. Of the 64 students 63 successfully passed their courses, and one did not. Final course grades for each Summer section are listed in Table 10.

Table 10

Final Course Grades: Summer 2019

Section	A	B	C	D	F	*N*
SOCI 002-001	9	5	0	0	0	14
SOCI 002-002	19	5	0	0	1	25
SOCI 020	17	7	1	0	0	25

All sections combined carry a 98.4% pass rate. SOCI 002-001 had a 100% pass rate with the class average of 91.86/A. SOCI 002-002 had a pass rate of 96%. One student did not pass this course (see Table 9). The class average for this section was 89.92/B. SOCI 020 had a 100% pass rate with the class average being 92.32/A.

Overall, of the 122 students surveyed, only 3 did not pass their online class. This resulted in an overall pass rate of 98%. The distribution of the combined course grades is presented in Table 11.

Table 11

Overall course grades

Section	N = 122
A	83
B	28
C	8
D	1
F	2

CUSE scores and course grades. This section will provide descriptive data for each student's CUSE score as well as her/his final course grade. Each section surveyed will be discussed with particular emphasis on the relationship between the student's CUSE score and their final course grade. While CUSE scores and course grades have already been discussed, it is necessary to examine the relationship between the two for hypothesis testing.

Late-Start SOCI 002. As stated above, 20 students completed the CUSE questionnaire for this course. The pass rate for this section was 100% with a class average of 92.95/A. However, the average CUSE score for this section was 49.45 which is consistent with low CSE. It should be noted that student 18 had the lowest CUSE score at 24 for this section, yet passed the course with 95/A. Likewise, student 8 had the next lowest CUSE core with 25 and passed the course with 88/B. The lowest course grade recorded for this section was student 2 with 76/C yet this student had a CUSE score of 57. While this is still consistent with low CSE, it is considerably higher than students 8 and 18. The descriptive data for this section is presented in Table 12.

Table 12

Late-Start SOCI 002

Participant	CUSE score (High/Low)	Final Course Grade
Student 1	72 (high)	98/A
Student 2	57 (low)	76/C
Student 3	52 (low)	87/B
Student 4	58 (low)	89/B
Student 5	31 (low)	89/B
Student 6	53 (low)	94/A
Student 7	68 (high)	93/A
Student 8	25 (low)	88/B
Student 9	71 (high)	97/A
Student 10	50 (low)	96/A
Student 11	34 (low)	85/B
Student 12	33 (low)	90/A
Student 13	64 (high)	101/A
Student 14	56 (low)	101/A
Student 15	56 (low)	82/B
Student 16	50 (low)	101/A
Student 17	44 (low)	97/A
Student 18	24 (low)	95/A
Student 19	48 (low)	101/A
Student 20	43 (low)	99/A

Late-Start SOCI 020. Sixteen students completed the CUSE questionnaire for this section. Sixteen students enrolled in this section completed the CUSE survey. Of the 16 students, two did not pass. The pass rate for this section was 85.8 with a class average of 92.95/A. However, the average CUSE score for this section was 48.31. This number is consistent with low levels of CSE. It should be pointed out that student 14 had the highest course grade at 103/A and also had the lowest CUSE score at 29. Student 11 also had a CUSE score of 29, but passed the class with 96/A. The next lowest CUSE score was student 13 with a score of 36. This student received a 97/A in the course. Yet, student 7 who had a similar score of 35 received 71/C. With respect to the two students who did not pass the course, the student with the D had a CUSE score of 72, which is the highest attainable score, while the student with the F has a CUSE score of 52. The descriptive data for this section is presented in Table 13

Table 13

Late-Start SOCI 020

Participant	CUSE score (High/Low)	Final Course Grade
Student 1	68 (high)	99/A
Student 2	43 (low)	77/B
Student 3	49 (low)	84/B
Student 4	72 (high)	60/D
Student 5	52 (low)	59/F
Student 6	50 (low)	100/A
Student 7	35 (low)	71/C
Student 8	49 (low)	83/B
Student 9	59 (low)	82/B
Student 10	55 (low)	77/C
Student 11	29 (low)	96/A
Student 12	54 (low)	96/A
Student 13	36 (low)	97/A
Student 14	29 (low)	103/A
Student 15	42 (low)	93/A
Student 16	51 (low)	97/A

Late-Start SOCI 028. Twenty-two students completed the CUSE questionnaire for this section. The pass rate for this section was 100% with a class average of 93.41/A. However, the average CUSE score for this section was 53.05. While this number is consistent with low levels of CSE, it was the highest score of all six sections surveyed. It should be noted that student 17 had the highest course grade with 102/A and a low CUSE score of 49. This is lower than the section average. Student 7 had the lowest CUSE score with 36 yet received a 90/A in the course. Students 6 and19 had the next lowest CUSE score with 40. However, student 6 finished the course with 95/A, and student 19 with a grade of 98/A. The lowest grade for this section was 79/C earned by students 8, 15, and 18. Of these three students, 8 and 18 had the highest CUSE score is the class with 65 and 72 respectively. Students 2, 9, 17, and 22 received a grade of 100 or higher. Yet, all four students recorded CUSE scores that are consistent with low levels of CSE. The descriptive data for this section is presented in table 14.

Table 14

Late-Start SOCI 028

Participant	CUSE score (High/Low)	Final Course Grade
Student 1	60 (high)	92/A
Student 2	59 (low)	100/A
Student 3	42 (low)	86/B
Student 4	69 (high)	88/B
Student 5	63 (high)	100/A
Student 6	40 (low)	95/A
Student 7	36 (low)	90/A
Student 8	65 (high)	79/C
Student 9	48 (low)	100/C
Student 10	62 (high)	94/A
Student 11	49 (low)	101/A
Student 12	48 (low)	95/A
Student 13	43 (low)	97/A
Student 14	67 (high)	98/A
Student 15	47 (low)	79/C
Student 16	48 (low)	95/A
Student 17	42 (low)	102/A
Student 18	72 (high)	79/C
Student 19	40 (low)	98/A
Student 20	48 (low)	96/A
Student 21	61 (high)	91/A
Student 22	58 (low)	100/A

Summer SOCI 002-001. Fourteen students completed the CUSE questionnaire for this section. The pass rate for this section was 100% with a class average of 91.86/A. However, the average CUSE score for this section was 44.71. This number is consistent with low levels of CSE. In fact, of the six sections served, this section recorded the lowest average for CUSE scores. It should be noted that student 12 had the lowest CUSE score with 27 yet received 98/A in the course. Student 14 had the second lowest CUSE score with 30 and received a 92/A in the course. Student 10 had a similar CUSE score with 31 and had a similar course grade with 91/A.

Student 5 had the higher course grade with 102/A yet recorded one of the lowest CUSE scores with 40. The highest CUSE scores in this section came from students 4 and 11. Student 4 recorded a CUSE score of 62 and received a course grade of 101/A, while student 11 had a CUSE score of 60 and a final course grade of 81/B. The descriptive data for this section is presented in table 15

Table 15

Summer SOCI 002-001

Participant	CUSE score (High/Low)	Final Course Grade
Student 1	56 (low)	92/A
Student 2	45 (low)	99/A
Student 3	50 (low)	83/B
Student 4	62 (high)	101/A
Student 5	40 (low)	102/A
Student 6	50 (low)	86/B
Student 7	39 (low)	84/B
Student 8	53 (low)	98/A
Student 9	37 (low)	85/B
Student 10	31 (low)	91/A
Student 11	60 (high)	81/B
Student 12	27 (low)	98/A
Student 13	46 (low)	94/A
Student 14	30 (low)	92/A

Summer SOCI 002-002. Twenty-five students completed the CUSE questionnaire for this section. This section had a pass rate of 96%. One student did not pass this course (see Table 9). The class average for this section was 89.92/B. However, the average CUSE score for this section was 49.88. This number is consistent with low levels of CSE. Student 25 did not pass the course. In fact, this student had the lowest CUSE score with 15 and also had the lowest course grade with 18/F. Students 7 and 22 had the second lowest CUSE score with 25. However, student 7 completed the course with one of the highest grades with 99/A, while student 22 received an 83/B in the course. Student 17 had the third lowest CUSE score with 34, yet passed the course with 95/A. Student 1 had the next lowest CUSE score with 38 and passed the course with 97/A. Students 10, 20, and 21 all passed the course with 100/A or higher. However, students 10 and 21 had two of the lowest CUSE scores with 42 and 36 respectively. Student 20 had a CUSE score of 52. While this score is consistent with low CSE, it is still higher than students 10 and 21. It should be noted that this section had the highest number of students that recorded high levels of CSE with 8 (Late-start SOCI 028 also recorded 8 students). Student 19 had recorded the highest CUSE score with 72 and passed the class with 96/A. Likewise, student 18 recorded the next highest CUSE score with 71 and also passed the course with 96/A. Student 3 recorded a CUSE score of 69 and passed the class with 91/A. However, student 14 recorded a CUSE score of 66 but passed the class with 84/B. The descriptive data for this section is presented in Table 16.

Table 16

Summer SOCI 002-002

Participant	CUSE score (High/Low)	Final Course Grade
Student 1	38 (low)	97/A
Student 2	60 (high)	92/A
Student 3	69 (high)	91/A
Student 4	58 (low)	82/B
Student 5	55 (low)	91/A
Student 6	67 (high)	93/A
Student 7	25 (low)	99/A
Student 8	38 (low)	81/B
Student 9	63 (high)	96/A
Student 10	42 (low)	101/A
Student 11	43 (low)	97/A
Student 12	57 (low)	93/A
Student 13	58 (low)	93/A
Student 14	66 (high)	84/B
Student 15	47 (low)	80/B
Student 16	44 (low)	93/A
Student 17	34 (low)	95/A
Student 18	71 (high)	96/A
Student 19	72 (high)	96/A
Student 20	52 (low)	100/A
Student 21	36 (low)	102/A
Student 22	25 (low)	83/B
Student 23	46 (low)	95/A
Student 24	66 (high)	100/A
Student 25	15 (low)	18/F

Summer SOCI 020. Twenty-five students completed the CUSE questionnaire for this section. This section had a 100% pass rate with the class average being 92.32/A. However, the average CUSE score for this section was 49.68. This number is consistent with low levels of CSE. It should be noted that student 11 had the lowest CUSE score with 16 yet passed the course with 95/A. Likewise, students 4 and 7 had the next lowest CUSE scores with 32 and 31 respectively. However, student 4 passed the course with 97/A, while student 7 passed the course with 95/A. Students 6 and 17 recorded the highest levels of CSE with scores of 72. However, student 6 passed the course with 88/B, while student 17 passed the course with 90/A. Students

19 and 22 earned the highest course grades with 102/A and 103/A respectively. However, student 19 recorded a CUSE score of 45, while student 22 recorded a CUSE score of 58. Both scores are consistent with low levels of CSE. In this section, five students recorded high levels of CSE: students 2, 6, 16, 17, and 25. Of the five, student 6 had the lowest course grade at 86/B followed by students 2 and 25 with 88/B, student 17 with 90/A, and student 16 with 99/A. It should be noted that the students with some of the highest course grades also had some of the lowest CUSE scores. The descriptive data for this section is presented in table 17.

Table 17

Summer SOCI 020

Participant	CUSE score (High/Low)	Final Course Grade
Student 1	59 (low)	99/A
Student 2	65 (high)	88/B
Student 3	48 (low)	72/C
Student 4	32 (low)	97/A
Student 5	36 (low)	81/B
Student 6	72 (high)	86/B
Student 7	31 (low)	95/A
Student 8	46 (low)	88/B
Student 9	53 (low)	98/A
Student 10	46 (low)	93/A
Student 11	16 (low)	95/A
Student 12	47 (low)	96/A
Student 13	50 (low)	98/A
Student 14	43 (low)	85/B
Student 15	39 (low)	95/A
Student 16	65 (high)	99/A
Student 17	72 (high)	90/A
Student 18	38 (low)	96/A
Student 19	45 (low)	102/A
Student 20	53 (low)	84/B
Student 21	45 (low)	90/A
Student 22	58 (low)	103/A
Student 23	57 (low)	93/A
Student 24	56 (low)	97/A
Student 25	70 (high)	88/B

Spearman's *r*. Likert data are ordinal and should be analyzed with non-parametric statistics because the distances between the response options are not consistent. Spearman's r_s determines the degree to which a relationship is monotonic. That is, Spearman's *r* measures the strength and direction of relationship between two continuous variables, two ordinal variables, or one continuous and one ordinal variable. This research consisted of two ordinal variables: the student's CUSE score and the student's final course grade. However, to determine if the present data set is appropriate for Spearman's *r* the data need to pass three assumptions: 1. The variables being measured are either continuous or ordinal, 2. The two variables are paired observations, and 3. There needs to be a monotonic relationship between the two variables. To determine this, a scatterplot of the two variables was performed to make sure there was a linear relationship between the two variables. The results of the scatterplot are shown in Figure 1.

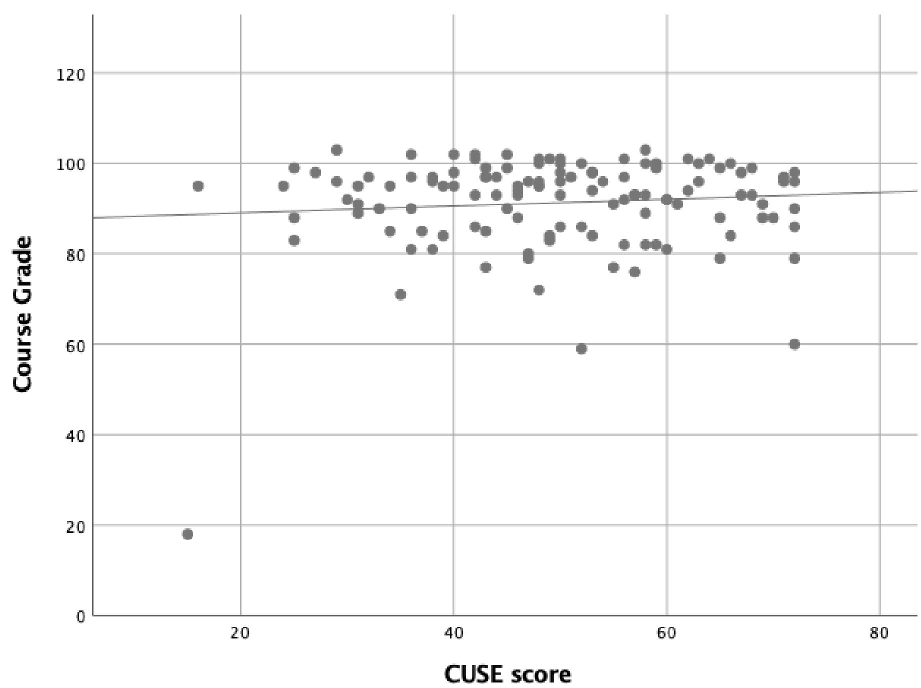

Figure 1. Simple scatter plot with fit line of course grade by CUSE score.

The scatter plot shown above shows a slight positive direction with a low linear relationship: r^2 = .009. However, it was determined that there was enough of a liner relationship to perform a Spearman's correlation coefficient. The analysis of the Spearman's *r* is shown in Table 11.

Table 18

Correlation

		CUSE score	Course Grade
CUSE score	Correlation Coefficient	1.000	-.011
	Sig. (2-tail)	.	.901
	N	122	122
Course Grade	Correlation Coefficient	-.011	1.000
	Sig. (2-tail)	.901	.
	N	122	122

With respect to Spearman's *r*, as the correlation coefficient gets close to 0 there is no relationship between the variables. Additionally, a negative *r* value suggests that as one variable gets larger the other variable gets smaller. This implies that as the CUSE score gets larger, the course grade gets smaller (lower). This suggests that there is no correlation between CUSE score and the student's course grade.

Spearman's rank-order correlation was run to assess the relationship between CUSE scores and course grades. One hundred twenty-two participants were recruited. Preliminary analysis showed the relationship to be monotonic, as assessed by visual inspection of a scatterplot. However, the analysis showed there was no statistically significant relationship between CUSE scores and course grades, r_s (122) = -.011, $p < .001$.

Independent sample t-test. To further corroborate this finding an independent sample t-test was performed on two sections: late-start spring SOCI 002 and 028. It was determined that it may be necessary to examine the CUSE score means of these two sections. SOCI 028 is a higher-level sociology course and, presumably, these students have taken other sociology courses which may affect their confidence level. There were 20 students in SOCI 002 and 22 in SOCI 028. The CUSE score for SOCI 028 (*M = 53.05, SD 10.764*) was higher than the CUSE score for SOCI 002 (*M = 49.45, SD 14.387*). The assumption of homogeneity of variances was violated, as assessed by Levene's test for equality of variances ($p = .394$). There is no statistically significant difference between the mean CUSE score of SOCI 002 and 028 $t(40) = -.922$, $p = .394$. Again, we fail to reject the null hypothesis that there is no relationship between higher levels of CSE and completion of online courses in California community colleges.

Chapter 4 Summary

This study examined if higher levels of CSE contributes to online course completion among online California community college students. Data for this study consisted of CUSE score and final course grades. The CUSE score was calculated from surveys administered to online students in six sociology classes at a California community college. The survey consisted of 12 questions with a six-point Likert response scale. Each question centered on their confidence in dealing with computer related problems. Overall, 122 student surveys were collected with 66 female respondents, 50 male respondents, five declining to state their gender, and one student who did not answer the question.

The data analysis of this study fit the applied research approach for a quantitative study. As such, a quantitative correlational design was the appropriate method to implement for this investigation. Correlational research designs address whether a significant difference in the relationship of a sample exists purely by chance or if the relationship is accurately reflected in the population. Therefore, Spearman's correlation coefficient (Spearman's *r*) was used to analyze the data. Analysis of Spearman's *r* showed there was no statistically significant relationship between CUSE scores

In addition, three questions were asked addressing the types of technology the students used, types of computer problems they normally experience, and their perceived level of computer experience. With respect to the first question, 100% of the respondents listed computers and cell/mobile phones as the type of technology they used the most. With respect to question two, most students reported that slow computers and/or slow internet was the problem they encounter the most. With respect to question three, over half of the students classified themselves as moderate or intermediate. However, it was determined that the CUSE score for this group was 47.12 which is consistent with low CSE. Additionally, one-third of the students surveyed viewed themselves as expert, advanced, or very proficient. The average CUSE score for this group was 56.44 which is also consistent with low levels of CSE.

Of the 122 students surveyed, only three did not pass their online course. This resulted in a 98% pass rate. Despite this high pass rate, 76% of students surveyed reported low levels of CSE. The average CUSE score for this group was 44.19. Conversely, only 24% of students surveyed reported high levels of CSE. The average CUSE score for this group was 66.69. Spearman's correlation coefficient was used to measure the relationship between students CUSE scores and their final course grade.

Chapter 5: Discussion and Conclusion

Introduction

The purpose of this chapter is to provide an overview of the findings of the study and a discussion of how these findings relate to the literature review presented in Chapter 2. Limitations of the study will also be discussed, as well as implications in findings applicable for future practice, policy, and theory. Additionally, recommendations for future research will also be presented. Furthermore, the researcher will share his insight, evaluations, and interpretation of the findings in this quantitative study and determine what the results mean to online learning in higher education. Moreover, the researcher will discuss how the study informed the literature, and how the results confirmed or added new knowledge to the learning community are also included in this chapter.

The research on self-efficacy and online learning environments has been predominantly related to computers and students' confidence in using technology associated with online learning (Zimmerman & Kulikowich, 2016) . In fact, self-efficacy has been used as a valid measure for predicting grade point averages and overall academic success (Thangarasu & DePaul, 2014). Additionally, studies show that perceived efficacy for using computers results in greater likelihood of people using them (Cai et al., 2017; Howard, 2014; Pellas, 2014). These studies also determined that as the quality of the experience increased so did one's self-efficacy for computers. This resulted in an increase in future usage of computers and had a direct impact on classroom performance (Hauser et al., 2012). This suggests that positive performance and technology related self-efficacy are directly related to student performance in online classes (Zimmerman & Kulikowich, 2016) and self-efficacy is important when evaluating digital natives (Malinovski, Vasileva, Vasileva-Stojanovska, & Trajkovik, 2014).

This is important because the current population of students served by California's Community College system is considered digital learners. This term reflects their ease and familiarity with digital technology. Therefore, it was reasonable to suggest that digital learners should have high levels of CSE and that these higher levels of CSE should influence completion rates. However, the data gathered in this study showed that it was not the case.

This study examined if a relationship existed between high levels of CSE and online course completion among online California community college students. For the purpose of this research, course completion was defined as those students who pass their online course with 70% (C) or better. The research question that guided this study asked: To what extent is there a relationship between higher levels of CSE and the completion of online courses between in California community colleges? This study was conducted from March-July 2019. The CUSE survey was administered during the first two weeks of the Spring (late-start) 2019 term and the Summer 2019 term. The CUSE scores were tabulated and compared to their final course grade at the conclusion of the Spring and Summer semesters.

Summary of the Results

This study used a quantitative correlational design to examine to what extent if any does a relationship exist between high levels of CSE and course completion. To address this research question, a 12-item CUSE Scale and three computer related questions were given to 122 students. The 12-item CUSE scale used a six-point Likert scale.

The CUSE score was calculated by adding the score for each question. The maximum score was 72. It was determined that scores 60–72 would be consistent with high levels of CSE while scores below 60 would be consistent with low levels of CSE. These numbers were derived from the CUSE scale developed by Cassidy and Eachus (2002). Cassidy and Eachus' original scale consisted of 30 questions on a six-point Likert scale. The respondent's response was totaled resulting in the total CUSE score. High levels of CSE were considered if the respondent's score was over 150 (83%) or higher. However, the present study used the CUSE questionnaire developed by Howard (2014) which showed to be more applicable to today's computer terminology. This scale consisted of 12 questions with a six-point Likert scale. Howard did not provide an equivalent threshold for low or high levels of CSE. So, Cassidy and Eachus was adopted. The max score for the scale used in this study was 72 making the 83% threshold 60.

This study showed that 76% of the students surveyed had CUSE scores consistent with low levels of CSE while 24% of the students surveyed had CUSE scores consistent with high levels of CSE. Furthermore, of the 122 students surveyed, only three students did not pass their online class, making the success rate 98%. This result was surprising because it runs contrary to the literature (Zimmerman & Kulikowich, 2016). However, CUSE scores between males and females were consistent with literature (Y. Bao, T. Xiong, Z. Hu, & M. Kibelloh, 2013a; Cai et al., 2017). That is, males had a higher CUSE score than did females. Analysis of the data using Spearman's correlations coefficient showed that there was no statistically significant relationship between high levels of CSE and final course grades.

Discussion of the Results

To what extent is there a relationship between higher levels of CSE and the completion of online courses between in California community colleges? After collecting the data and performing the Spearman's correlation coefficient, it was determined that there was no statistically significant relationship between CUSE scores and the overall course grades, r_s (122) = -.011, $p < .001$. This result was surprising considering that the students surveyed are considered digital learners. That is, presumably, these students have been exposed to computers and digital media their whole lives and, as a result, should have confidence in their ability to solve computer-related problems. However, the low CUSE scores show that this is not the case. In fact, these low scores could be the result of the CUSE scale not accurately measuring the students CSE. This will be explored below under recommendations for further research.

The modern collegiate student uses digital technologies and the Internet in all aspects of their daily life including school, work, and leisure activities (Gallardo-Echenique et al., 2015). In fact, they represent the first generation to grow up with this new technology and they have spent most of their lives surrounded by computers and digital communication technology. The CUSE scale is designed to measure the amount of confidence individuals have in their ability to solve computer related problems. The data collected in this study suggest that students lack the confidence they need to solve computer related problems despite passing their courses. This study examined if there was a relationship between higher levels of CSE and course completion. The findings in this study suggest that levels of CSE, such as high and low, do not adequately describe the levels of self-efficacy exhibited by our students. In fact, self-efficacy with respect to mobile technology and other forms of electronic media, may be enough for students to be successful in online courses.

With respect to gender, the data collected were consistent with the literature. On average, females tend to have lower levels of CSE than males. Of the 122 students surveyed, 66 identified as female, 50 as male, and six declined to state. Female students had a mean CUSE score of 47.11, while males had a mean score of 52.26 (Bao et al., 2013a; Cai et al., 2017).

In addition to the CUSE scale, three questions were asked regarding the types of technology students normally use, what types of computer problems they normally encountered, and did they feel their computer experience level was. The first question asked: "What type of technology do you normally use?" Every student surveyed listed computers and cell/mobile phones as the type of technology they normally use. These data were expected considering how ubiquitous computers and mobile technologies are today. This was followed by gaming systems, the Internet, and television. These responses are typical of digital learners and underline the cultural importance of these devices.

Question two asked, "What type of computer problems do you normally experience?" With respect to this question, almost half of the students reported that their main computer problem was slow computers, slow internet or both. With regards to computers, "slow" or "slowing computer" was mentioned 25% of the time. With respect to the internet, "slow," "poor," or "connectivity" issues was mentioned 23% of the time. These comments are not surprising considering we are dealing with digital learners and most of their computer and mobile related activity involves the Internet.

Question three asked, "What is your experience level with computers?" For this question, there were 118 responses with four students not responding. Of the 118 students, 7.6%, listed their experience level with computes as none, nearly none, not much, or not too well. The average CUSE score for these students was 38.44 which is consistent with a low CSE score. This score was unexpected considering these students are classified as digital learners and, presumably, grew up with digital technology. One possible explanation could be immigrants who come to the United States with little or no prior computer experience. The college used in this study is extremely diverse with 38% of the student population being either Hispanic or Asian. The researcher is a faculty member at the study site and knows that many of these students are immigrants. However, according to California state law, colleges and universities are not allowed to ask students their immigration status. So, the actual numbers of immigrants attending this college is unknown. Additionally, socioeconomic factors could have also contributed to this low level of experience. While this college is surrounded by affluent neighborhoods, the socioeconomic factor cannot be ruled out.

Sixty-eight students, or 57.6% of students surveyed, classified themselves as moderate or intermediate with respect to their experience level with computers. These students also had a low CUSE score with an average score of 47.12. These findings are interesting and uncharacteristic of digital learners. Gallardo-Echenique et al. (2015) noted that today's students use digital technologies and the Internet in all aspects of their daily life including school, work, and leisure activities. Yet, according to the low CUSE scores, these students lack confidence in computer related tasks. Again, the data demonstrates that higher levels of CSE are not necessary to pass online courses.

Finally, 34.7% of the students rated their computer experience as expert, advanced, perfect, genius, high, experienced, very proficient, or listed themselves as 9 or 10 on an ordinal scale. However, their average CUSE score was 56.44. This number is still consistent with a low CUSE score. This result was surprising considering the very high confidence these students had in their computer experience level. Again, this result suggests that higher levels of CSE are not an important factor for success in today's online courses.

Based on the data above, it is clear that most students have very little confidence in their ability to solve computer related problems as it relates to online learning (see Appendix A). The low CUSE scores suggest this. These results were quite unexpected considering these students are classified as digital learners. While it remains unclear why the CUSE scores are low, it could however, force researchers to reevaluate our assumptions of digital learners. That is, when asked, “What type of technology do you normally use?” computers and mobile technology were cited by every student surveyed. However, a majority of students reported low levels of CSE. Students can use computers but, according to this study, they have very little confidence in their ability to solve computer related problems. As a result, this study shows that high levels of CSE are not needed to be successful in online courses.

Discussion of the Results in Relation to the Literature

It has been well documented that self-efficacy is a valid measure for predicting grade point averages and overall academic success (Thangarasu & DePaul, 2014). Because of the significant role online learning plays in higher education, self-efficacy has become a useful tool for examining student confidence and successful completion of the course. As identified in the literature, factors such as high levels of CSE, student success, and completion rates among digital learners are important concerns when considering student success in online learning (Dang et al., 2016; Wilson & Narayan, 2016; Zimmerman & Kulikowich, 2016). This section will discuss these three factors and examine the results of this study with respect to these factors.

There is considerable debate in the literature regarding the role any type of self-efficacy plays in predicting success (DeTure, 2004; Hodges, 2008; Puzziferro, 2008; Zimmerman & Kulikowich, 2016). It is argued that for students to be successful in online courses they need both CSE and ASE. However, other researchers maintain that self-efficacy is actually a component of self-esteem and that factors like academic achievement can also be influenced by socio-economic status, learning styles, motivation, school related factors, and social behavior despite how much self-efficacy the student has (Balami, 2015). With this in mind, there could have been unforeseen factors such as socioeconomic factors that could have prevented students from having computers at home. This could have had an effect on their confidence levels.

High levels of computer self-efficacy. The use of CUSE scales has been a reliable source of assessment for several decades (Cassidy & Eachus, 2002; Compeau & Higgins, 1995; Howard, 2014; Howard & Jayne, 2015). In fact, their reliability has prompted researchers, instructors, and administrators to use CUSE scales for general assessment and research purposes. For this reason, the CUSE scale by Howard (2014) was used to address the research question.

Computer self-efficacy is known to play a role in academic performance and course outcomes. However, the significance of this role is unknown, and the literature is inconsistent in this respect. While some research supports that higher levels of CSE increase academic performance and course outcomes, others do not. For example, Zimmerman and Kulikowich (2016) showed a slight positive correlation between CSE and student performance in online courses. Research by Wang, Shannon and Ross (2013) also supported this. However, studies by DeTure (2004) and Puzziferro (2008) suggest that CSE does not affect course outcomes. In particular, DeTure examined five online sections from a community college in Florida. The demographics were similar to the present study. DeTure was trying to determine if specific learner attributes were useful in predicting student success in online learning. To determine which attributes were useful, DeTure administered a Group Embedded Figures Test (GEFT), which determines one's cognitive style, and an Online Technologies Self-efficacy (OLSE) Scale. DeTure determined that cognitive style scores and OLSE scores were poor predictors of student success in online courses. Likewise, Puzziferro, came to the same conclusions. She surveyed 163 online sections from a southeastern community college. Puzziferro administered a OLSE scale and a Motivated Strategies for Learning Questionnaire and determined that online technologies self-efficacy scores were not correlated with student performance.

The results of this study supports the conclusions reached by DeTure (2004) and Puzziferro (2008) in that most students did not have high levels of CSE and that this did not predict students' ability to pass their course. In fact, some of the students with the lowest CUSE scores received the highest grades in their courses. Of the 122 students surveyed, 93 had a CUSE score consistent with low levels of CSE. The average CUSE score for this group was 44.19. Only 29 students had CUSE scores that were consistent with high levels of CSE. The average score for this group was 66.69. SOCI 028 (late-start spring) had the highest CUSE score of 53.05. The other sections ranged from 48.31 to 49.88. Even though 76% of the students surveyed reported low CUSE scores, 98% of them still passed their course and many passed with an A. This was an unexpected finding of the study. These students are digital learners and, as such, have been around computes most of their lives. From this we can assert that their ability to use computers is independent of their ability to solve computer related problems.

Unfortunately, this study supports the inconsistency in the literature regarding the role of high levels of CSE. While it was not surprising that high levels of CSE did not influence their ability to pass the course, it was surprising that most of the students reported low levels of CSE. These students are digital learners and have been enculturated with digital technologies their whole lives. However, despite the low levels of CSE, many of these students still successfully passed their courses with extremely high grades. The implication of this is that the CUSE scale used in this study did not accurately measure students' CSE with respect to online learning. It would seem that the amount of self-efficacy they already have with respect to their mobile devices and other electronic media, is enough to be successful in their online courses.

Student success. The literature shows that students who are confident in themselves and their ability will have a strong sense of self-efficacy (Cai et al., 2017). Therefore, students who have higher levels of self-efficacy should experience greater success. Conversely, students with lower levels of self-efficacy will have more difficulty in meeting challenges and being successful. However, the results of this study showed that there is no relationship between high levels of CSE and student success. This section will provide examples from each section demonstrating the lack of influence CSE had on their student success.

In SOCI 002 (late-start spring) student 18 had the lowest CUSE score at 24. However, this student passed the course with 95/A. This student also reported that their level of computer experience was “nearly none.” Despite having little confidence in their ability to solve computer related problems, this student has no problem passing their course. Likewise, student 19 had a CUSE score of 48 yet passed the course with 101/A. This student reported their computer experience level as “intermediate” and that they were “comfortable solving most issues.” Be that as it may, this student still reported low levels of CSE. These results demonstrate that higher levels of CSE are not needed to be successful in passing their online courses. The use of mobile technology and ability to navigate other forms of digital media was enough self-efficacy to pass their courses.

In SOCI 020 (late-start spring), student 14 had a CUSE score of 29 yet passed the course with 103/A. This student also reported that their computer-related experience was simply for writing essays and research but limited experience beyond that. Student 11 in the same section also has a CUSE score of 29 yet passed the course with 96/A. This student reported that s/he barely had any computer experience. Student 11 in SOCI 020 (summer) had a CUSE score of 16 yet passed the course with 95/A. These are impressive grades considering that this student had very little confidence in their ability to solve computer related problems as demonstrated by her/his low CUSE score.

SOCI 028 (late-start spring) had the highest mean CUSE score of all the sections. Student 7 had the lowest CUSE score at 36 yet passed the course with 90/A. This student reported that her/his computer-related experience was “moderate.” However, student 8 had a CUSE score of 65 which is consistent with higher levels of CSE but earned a 79/C in the course. This student reported their computer-experience as “7 out of 10.” While this student had confidence in their selves as indicated by the higher levels of CSE, they only earned a C in the course. As demonstrated above, there is no relationship between their course grades and their CUSE scores.

In other examples, student 10 in SOCI 002-001 (summer) had a CUSE score of 31 which is consistent with low levels of CSE. However, this student passed the class with 95/A. Not unlike the information presented above. However, this student reported having no experience with computers. In another example, student 4 in SOCI 020 (late-start spring) had a CUSE score of 72 which is the highest attainable score. When asked about their level of computer experience, this student reported “genius.” However, this student did not pass the course (60/D). Again, CSE was not a contributing factor.

SOCI 002-002 (summer) had the lowest CUSE score recorded with student 25. This student reported a CUSE score of 15 and this student did not pass the course (18/F). This student reported that their computer-related experiences were “in the middle when it comes to computers.” While this statement implies that this student had come confidence in themselves, it is not reflected in their CUSE score or final course grade. Student five in this section reported a CUSE score of 55 and passed the course with 91/A. While this score is still consistent with low levels of CSE, it is higher than most. When asked about their computer-related experience, this student reported that they were at “a basic level.” Clearly, there is tremendous inconsistency between students' CUSE scores, their course grades, and how they view their level of computer experience.

SOCI 020 (summer) had 25 students. The lowest course grade in this section was student three who had a CUSE score of 48 and a course grade of 72/C. This student referred to their computer experience as intermediate. The CUSE score for student eight was slightly lower at 47 yet this student passed the course with 88/B. This student recorded high levels of computer-related experience. Still, student 19 had a CUSE score of 45, slightly lower than student three and eight yet this student passed the course with 102/A. However, this student listed their computer-related experience as "pretty efficient." Student 11 had the lowest CUSE score of section with 16. Yet, this student passed the course with 95/A. This student reported that their only experience with computers was in school only. Again, there is tremendous inconsistency between student's CUSE scores and their course grades.

The data collected in this study suggests that higher levels of CSE are not necessary to pass online courses. Every student surveyed listed mobile devices as their primary form of technology. As a result, it would seem that any amount of CSE is an advantage and the self-efficacy students possess with regards to their mobile technology and other electronic devices is enough to be successful.

Digital learners. An examination of the literature shows that the unifying characteristics of digital learners is their innate comfort and confidence using technology (Ripley, 2013). However, as this study shows, 76% of the students surveyed had low levels of CSE. With respect to computer-related experience, most students classified themselves as intermediate. The research on self-efficacy and online learning environments has been predominantly related to computers and student's confidence in using technology. Studies show that CSE results in greater likelihood of people using computers and that they will be more confident in handling the computers (Achim & Al-Kassim, 2015; Jan, 2015). The data collected in this study suggests that higher levels of CSE are not necessary to pass their online courses. Many students self-reported their computer-related skills as intermediary or expert. However, these students also reported CUSE scores that were consistent with low levels of CSE. This is uncharacteristic for digital learners. After all, research shows that the unifying characteristic of digital learners is their innate comfort and confidence in using technology (Ripley, 2013).

Positive performance and technology related self-efficacy are directly related to student performance in online classes (Zimmerman & Kulikowich, 2016). However, not everyone is convinced that perceived self-efficacy predicts success. For example, Hodges (2008) stated, "Computer use is obviously important in successful completion of an online course, but self-efficacy for computer use in a general sense is most likely not as predictive of success in the course as a more specific measure" (p. 21). Hodges argues that any scale used to measure self-efficacy for online learning needs to be tailored for the specific learning situation being studied. Because mobile technologies and the prevailing technologies of the Internet, students already have high levels of these self-efficacies. However, the CUSE scale used in this study was examining confidence with computers. For example, question 1 of the CUSE scale asked, "I can always manage to solve difficult computers problems if I try hard enough." Question 2 asked, "If my computer is 'acting up,' I can find a way to get what I want" (see Appendix A). Every question asks about the students' confidence level with computers only. The data collected for this study tends to support Hodges' comments. While there is no doubt that students are confident in their ability to use a computer and to use mobile technology, solving computer related problems seems to be another matter and it does not affect their ability to pass their online courses. As a result, the design of the CUSE scale used in this study might not have accurately measured students CSE as it pertains to online learning.

Limitations

There are several limitations associated with the present study. First, data were collected at one California community college and should not be reflective of all California community colleges. Secondly, institutional approval from the study site did not occur until after the Spring 2019 semester started. This became an issue because it was necessary to have the CUSE survey administered at the beginning of the semester before students had the opportunity to get too deep into their online course. Unfortunately, this dramatically reduced the number of course offerings available for research. Classes were chosen based on instructors who volunteered their courses. For this study, only one instructor volunteered. This same instructor also volunteered their courses for the summer 2019 semester. The results might have been different if courses from multiple instructors were used. Third, it is highly possible that students in this study are former or current students. This could have biased the students' responses. Another limitation can be considered because only one discipline—sociology—is represented in this study. Additional disciplines, such as computer related disciplines, might have produced different results. Finally, there is a lack of range within the final course grades and the study population, resulting in the scores being statistically insignificant.

Implications of the Results for Practice, Policy, and Theory

The intention of this study was to examine the relationship between CSE and completion rates in online courses in the California community college system. The purpose of the research was to examine if higher levels of CSE are a factor in completion rates given that today's student are digital learners. The results of this study suggest that there is no relationship between high levels of CSE and course completion rates. The findings revealed that higher levels of CSE are not necessary to pass online courses. The results suggest that CSE related to mobile technology and other forms of electronic media are enough to be successful in online courses. This section will examine the results of this study and the future implications with respect to practice, policy and theory.

Implication of the results for practice. Online education has become an important component in higher education (Meyer, 2014). As of 2015, nationwide, more than one quarter of all undergraduates were enrolled in online courses (McFarland et al., 2017). Furthermore, 12% of all undergraduates are exclusively enrolled in online education (McFarland et al., 2017). The amount of students enrolled in online courses is staggering and this number is projected to increase (McFarland et al., 2017). In the context of online learning, self-efficacy is especially important. Online learning requires more discipline and experience in technology (Jan, 2015). Because self-efficacy is concerned with a person’s confidence in their abilities to complete certain tasks and reach specific goals, the examination of self-efficacy has been standard practice for online educators, administrations, and Learning Management System developers.

However, the results of this study clearly show that there is no relationship between CSE and online course completion. In fact, a majority of students had CUSE scores that were consistent with low CSE implying that they lack confidence in their ability to solve computer related problems. Be that as it may, they still successfully passed their class. Moreover, most passed with an A. The implications of this conundrum are perplexing. How can one have little to no confidence in their ability to solve computer related problems and sill pass an online course (which requires knowledge about computers) with an A? It would seem that CSE with respect to mobile technology and other forms of electronic media provides enough confidence for students to be successful in their online courses.

However, this does not change the fact that these digital learners still reported low levels of CSE. Therefore, it would seem that a lack of confidence in one's ability to solve computer related problems does not mean that students cannot use computers adequately. The participants in this study use computers/technology every day for information, social media, and playing videogames. Clearly there are other forms of self-efficacy one needs to consider and perhaps, these forms of self-efficacy are more important than CSE with respect to online courses. As Hodges' (2008) suggest, when constructing a scale to measure CSE, it must be tailored to for the specific learning situation being studied. The CUSE scale used in this study measured confidence in computer use and was shown to be inaccurate in this learning situation.

There is no doubt that more research is needed in the area of CSE and online course work. The practice of considering the importance of CSE needs to be reevaluated especially with respect to today's student and the ubiquity and influence of mobile technology. Other forms of self-efficacy need to be investigated and researchers need to redefine what CSE is for today's digital learner.

Implication of the results for policy. Self-efficacy plays a vital role in people's success and research shows that successful people have higher levels of self-efficacy (Bandura, 1997). Considerable research has been conducted into the importance of self-efficacy in general and the role of the CSE in particular (Alqurashi, 2016; Pellas, 2014; Zimmerman & Kulikowich, 2016). With respect to CSE, research shows that an increase in students' CSE results in higher levels of course satisfaction, higher grades, more motivation and a better attitude (Prior et al., 2016). Identifying higher levels of self-efficacy in general and CSE in particular, has played an important role in developing policy around online courses. In fact, publishers routinely survey students in terms of their self-efficacy to develop and design Learning Management Systems (examples of Learning Management Systems are Angel, Blackboard, Canvas etc.) (D. Garnier, personal communication, December 4, 2017). Because computers are the backbone of online courses, CSE has played a significant role in policy development. However, considering the results of this study, when measuring CSE researchers must tailor the scale to specific learning situation. Questions need to consider the role of mobile technologies and other forms of digital media if they want an accurate representation of student's CSE.

By their nature, digital learners already possess some computer related skills necessary for success in online courses. Based on the data collected in this study, higher levels of CSE were not a determining factor in the success of digital learners. With respect to this study, on average, students surveyed had low CUSE scores yet, the combined completion rate for all of the three courses surveyed was 97.5%. The present study only examined the courses from one instructor. Courses with similar pass rates might want to consider the level of difficulty for future courses. Additionally, policy makers need to consider developing online courses with curriculum that is more robust and challenges digital learners. For example, using peer replies to critically analyze and demonstrate understanding of the material.

Implication of the results for theory. Bandura (1977) suggests that there are four sources of information that individuals use to gauge their efficacy: performance outcomes, vicarious experiences, verbal persuasion, and physiological feedback. These four sources guide individuals as they determine whether or not they have the capability to accomplish specific tasks (Bandura, 1997). Preassembly, then, these characteristics are fundamental when considering the self-directed nature of online education. The first source of information-performance outcomes—is the most important source of information according to Bandura (1977) and involves people learning from past experiences and building on them. In this study, three courses (six sections) were studied. SOCI 002, 020, and 028 are not introductory courses. In fact, they represent slightly higher levels of sociology. This suggests that students have already had some exposure to sociology and, online courses in general. Yet, despite this, the CUSE scores were low for 75% of students surveyed. Therefore, it would seem that previous exposure to online sociology courses did not influence the CUSE scores of the present study. This reinforces the conclusion that CSE from mobile devices and other electronic media were enough to provide students with the confidence they need to be successful in their online courses.

As educators, we all want our students to be successful. As online educators, this becomes especially difficult because of the lack of F2F interaction we have with our students and because students must possess both academic and CSE to be successful in online learning (Broadbent & Poon, 2015). Online learning requires that students use technology successfully. This study does show that despite being digital learners, a majority of students do not have confidence in their ability to solve computer related problems. Interestingly, this lack of confidence does not affect their ability to pass their online courses. The data collected suggests that CSE related to mobile technology and other forms of electronic media is enough to be successful in online courses. Future theoretical models examining different levels of CSE for digital learners, for example, low versus high, should need to be considered.

Recommendations for Further Research

If CSE plays a role in academic performance and course outcomes as suggested in the literature, then, based on the results of this study, a new approach in defining and understanding CSE might be needed. From the surveys collected, self-efficacy of mobile technology was the unifying theme for all students. As a result, researchers examining the role of CSE must tailor the scale to the specific learning situation being observed. The scale must develop questions that consider the role of mobile technologies and other forms of digital media if they want an accurate representation of students' CSE. The present study demonstrated that confidence with mobile technology and other forms of digital media was all the self-efficacy students needed to be successful in their courses.

Future researchers might want to consider the amount of time students spend online looking at the course material. That is, is there a relationship between levels of CSE and the amount of time spent online engaging in the course material. Future researchers will also need to consider the manner and types of courses chosen. Classes should be multidisciplinary and not limited to one department.

With respect to digital learners, confidence in computer skills is irrelevant when it comes to online learning. The true measure of success could be in the self-efficacy of mobile technology. That is, proficiency with their mobile technology could be giving students all the confidence they need to accomplish the computer related tasks necessary for online courses. For example, Canvas is the Learning Management System (LMS) used by all community colleges in California. This LMS also has an app that students can download to their phone. While some applications, like test taking, are not recommended (due to the instability of the app) students can complete many assignments using the app. As a result, mobile technology self-efficacy might be a better measure of online success rates.

With this in mind, a more multi-faceted approach for understanding the role of CSE in online courses might be necessary. As mentioned above, Hodges (2008) stated, "Computer use is obviously important in successful completion of an online course, but self-efficacy for computer use in a general sense is most likely not as predictive of success in the course as a more specific measure" (p. 21). The present study supports these conclusions. It seems that, at least for this study, students' lack of confidence in their ability to solve computer related problems, as demonstrated by their low CUSE scores, should have no problem passing a college level online course where computers are the primary medium. The confidence they do possess is in their ability to navigate problems with respect to their mobile technology. Perhaps this form of self-efficacy—mobile technology self-efficacy—is enough to give students the confidence their need to be successful in online courses.

When considering the role of CSE as a predictor of success in online courses, it might be necessary to take a more multi-faceted approach. For example, Shen et al. (2013) suggest that there are five dimensions of online learning self-efficacy: (a) self-efficacy to complete an online course, (b) self-efficacy to interact socially with classmates, (c) self-efficacy to handle tools in a Course Management System (CMS), (d) self-efficacy to interact with instructors in an online course, and (e) self-efficacy to interact with classmates for academic purpose. To truly examine the role of CSE in online learning, it might be necessary to take this more robust approach.

Today's student uses digital technologies and the Internet in all aspects of their daily life including school, work, and leisure activities (Gallardo-Echenique et al., 2015). In fact, they represent the first generation to grow up with this new technology and they have spent most of their lives surrounded by digital communication technology. However, students' today are on a continuum of technological access irrespective of age and most of them vary with respect to skill, ease of use, and comfort level. However, irrespective of their skill, ease of use, and comfort level, 97.5% of the students successfully completed the courses in this survey. In fact, 91% of all student surveyed received and A or B. As a result, we might be making online courses too easy.

Conclusions

In the context of online learning, self-efficacy is especially important. Online learning is self-directed and requires more discipline and experience in technology (Jan, 2015). Because self-efficacy is concerned with a person's confidence in their abilities to complete certain tasks and reach specific goals, it has huge implications for online educators. As a result, examining the self-efficacy of the students in online education has become an important measure.

However, while there is considerable research on self-efficacy in general and CSE in particular, there is little discussion on the relationship between CSE and digital learners. Digital learners, by their very nature, already possess some computer related skills necessary for success in online courses. With this in mind, it is important to examine the relationship between higher levels of CSE online course completion rates.

The purpose of the research was to examine if higher levels of CSE are a factor in completion rates given that today's student are digital learners. Data for this study consisted of CUSE score, three open-ended questions, and final course grades. The CUSE score was calculated from surveys administered to online students in six sociology classes. The survey consisted of 12 questions with a six-point Likert response scale. Each question centered on their confidence in dealing with computer related problems. In addition, three qualitative questions were asked addressing the types of technology the students used, types of computer problems they normally experience, and their perceived level of computer experience. Overall, 122 student surveys were collected. However, the analysis showed there was no statistically significant relationship between CUSE scores and course grades. The data presented here demonstrates that higher levels of CSE have no influence on a student's ability to pass their online courses. Instead, the CSE derived from mobile technology and other digital media provides enough confidence for students to pass their online courses. Future research should focus on the design of CUSE scales. These scales must be designed to measure the CSE for the specific study in question.

As new data becomes available, there is no doubt that the views and opinions on CSE will change. The goal of this study was to provide insight into the role higher levels of CSE play in online course completion rates. While the data collected in this study showed that there was no relationship between higher levels of CSE and course completion rates, the data did show that higher levels of CSE were not need. Furthermore, this study showed that the CUSE scale used did not adequately measure the students' CSE. The data collected demonstrated that the CSE digital learners already possess from their mobile technology and other forms of digital media was enough to successfully pass their online courses. It is the hope of the researcher that this study will augment the growing body of literature, to provide some insight into the role of CSE and course completion rates, and encourage future researchers to carefully consider their CUSE scale and what they intend to measure.

References

Achim, N., & Al-Kassim, A. (2015). Computer usage: The impact of computer anxiety and computer self-efficacy. *Procedia-Social and Behavioral Sciences, 172*, 701–708. doi:10.1016/j.sbspro.2015.01.422

Adams, K. A., & Lawrence, E. K. (2015). *Research methods, statistics, and applications*. Thousand Oaks, CA: SAGE Publications.

Aktürk, A. O. (2014). A study on epistemological beliefs of community college students and their self-efficacy beliefs regarding education use of the internet. *Education, 134*(3), 426–442.

Al-Azawei, A., & Lundqvist, K. (2015). Learning differences in perceived satisfaction of an online learning: an extension to the technology acceptance model in an Arabic sample. *The Electronic Journal of e-Learning, 13*(5), 408–426.

Alqurashi, E. (2016). Self-efficacy in online learning environments: A literature review. *Contemporary Issues in Education Research, 9*(1), 45–51. doi:10.19030/cier.v9i1.9549

Annual/term student count report. (2018). *California Community College System.* Retrieved from https://datamart.cccco.edu/Students/Student_Term_Annual_Count.aspx

Atchley, W., Wingenbach, G., & Akers, C. (2013). Comparison of course completion and student performance through online and traditional courses. *The International Review of Research in Open and Distance Learning, 14*(4), 104–116. Retrieved from http://www.irrodl.org/index.php/irrodl/issue/view/58

Balami, Y. G. (2015). Relationship between self-efficacy belief and academic achievement of distance learners in National Teachers Institute (NTI) Adamawa State, Nigeria.

International Journal of Education and Practice, 3(4), 80–84. doi:10.18488/journal.61/2015.3.2/61.2.80.84

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215.

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

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes, 50*, 248–287. doi:10.1016/0749-5978(91)90022-L

Bandura, A. (1995). Exercise of personal and collective efficacy in changing societies. In A. Bandura (Ed.), *Self-efficacy in changing societies* (pp. 1–45). New York, NY: Cambridge University Press.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: Worth Publishers.

Bao, Y., Xiong, T., Hu, Z., & Kibelloh, M. (2013a). Exploring gender differences on general and specific comptuer self-efficacy in mobile learning adoption. *Journal of Educational Computing Research 49*(1), 111–132. doi:doi.org/10.2190/EC.49.1.e

Bao, Y., Xiong, T., Hu, Z. Y., & Kibelloh, M. (2013b). Exploging gender differences in general and specific computer self-efficacy in mobil learning adoption. *Journal of Educational Computing Research*, *49*(1), 111–132. doi:http://dx.doi.org/10.2190/EC.49.1.e

Bates, R., & Khasawneh, S. (2007). Computers in human behavior: Self-efficacy and college students' perceptions and use of online learning systems. *Computer in Human Behavior*, *23*(1), 175–191. doi:10.1016/j.chb.2004.04.004

Bellini, C. G. P., Isoni Filho, M. M., de Moura Junior, P. J., & Pereira, R. (2016). Self-efficacy and anxiety of digital natives in face of compulsory computer-mediated tasks: A study about digital capabilities and limitations. *Computers in Human Behavior, 59*, 49–57. doi:doi:10.1016/j.chb.2016.01.015

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *Internet and Higher Education, 27*, 1–13.

Bullen, M., & Morgan, T. (2011). Digital learners not digital natives. *La Cuestión Universitaria, 7*, 60–68.

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education, 105*, 1–13. doi:10.1016/j.compedu.2016.11.003

Cassidy, S., & Eachus, P. (2002). Developing the computer user self-efficacy (CUSE) scale: Investigation the relationship between computer self-efficacy, gender and experience with computers. *Journal of Educational Computing Research, 26*(2), 133–153. doi:10.2190/jgjr-0kvl-hrf7-gcnv

Chang, C-S., Liu, E. Z.-F., Sung, H.-Y., Lin, C.-H., Chen, N.-S., & Chen, S.-S. (2014). Effects of online college student's internet self-efficacy on learning motivation and performance. *Innovations in Education and Teaching International*, *51*(4), 366–377. doi:10.1080/14703297.2013.771429

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and test. *MIS Quartely, 19*(2), 189–211. doi:10.2307/249688

Correia, J., Compeau, D., & Thather, J. (2016). Implications of technological progress for the measurement of technology acceptance variables: The case of self-efficacy. *DIGIT, 6*, 1–9.

Dang, Y., Zhang, Y., Ravindran, S., & Osmonbekov, T. (2016). Examining student satisfaction and gender differences in technology-supported, blended learning. *Journal of Information Systems Education, 27*(2), 119–130.

DeTure, M. (2004). Cognitive style and self-efficacy: Predicting student success in online distance education. *The American Journal of Distance Learning, 18*(1), 21–38.

Erdogan, Y., Bayram, S., & Deniz, L. (2008). Factors that influence academic achievement and attitudes in web based education. *International Journal of Instruction, 1*(1), 31–47.

Faul, F., Erdfelder, E., Lang, A.-G., & Buhner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*(2), 175–191.

Gallardo-Echenique, E. E., Marqués-Molías, L., Bullen, M., & Strijbos, J.-W. (2015). Let's talk about digital learners in the digital era. *International Review of Research in Open and Distributed Learning, 16*(3), 156–187.

Gay, L. R., Mills, G. E., & Airasian, P. (2012). *Educational research: Competencies for analysis and application*. Boston, MA: Pearson Higher Ed. .

Goulão, M. d. F. (2014). The relationship between self-efficacy and academic achievement in adults' learners. *Athens Journal of Education, 1*(3), 237–246.

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, 11*, 141–154.

Hodges, C. B. (2008). Self-efficacy in the context of online learning environments: A review of the literature and directions for research. *Performance Improvement Quarterly, 20*(3/4), 7–25. doi:10.1002/piq.20001

Howard, M. C. (2014). Creation of a computer self-efficacy measure: Analysis of internal consistency, psychometric properties, and validity. *Cyberpsychology, Behavior, and Social Networking, 17*(10), 677–681. doi:10.1089/cyber.2014.0255

Howard, M. C., & Jayne, B. S. (2015). An analysis of more than 1,400 articles, 900 scales, and 17 years of research: The state of scales in Cyperpsychology, Behavior, and Social Networking. *Cyberpsychology, Behavior, and Social Networking, 18*(3), 181–187. doi:10.1089/cyber.2014.0418

Jan, S. K. (2015). The relationship between academic self-efficacy, computer self-efficacy, prior experience, and satisfaction with online learning. *The American Journal of Distance Learning, 29*(1), 30–40. doi:10.1080/08923647.2015.994366

Kennedy, D. M., & Fox, B. (2013). ‘Digital natives’: An Asian perspective for using learning technologies. *International Journal of Education and Development using Information and Communication Technology (IJEDICT), 9*(1), 64–79.

Kuo, Y.-C., Walker, A. E., Schroder, K. E. E., & Belland, B. R. (2014). Interaction, internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *Internet and Higher Education, 20*, 35–50. doi:10.1016/j.iheduc.2013.10.001

Lee, C.-Y. (2015). Changes in self-efficacy and task value in online learning. *Distance Education*, *36*(1), 59–79. doi:10.1080/01587919.2015.1019967

Leedy, P. D., & Ormrod, J. E. (2019). *Practical research: Planning and design* (12th ed.). New York, NY: Pearson.

Lin, Y.-C., Liang, J.-C., Yang, C.-J., & Tsai, C.-C. (2013). Exploring middle-aged and older adults' sources of Internet self-efficacy: A case study. *Computers in Human Behavior, 29*, 2733–2743. doi:10.1016/j.chb.2013.07.017

Loar, E. A. (2018). Computer self-efficacy revisited. *Journal of Instructional Research, 7*, 55–59. doi:doi.org/10.9743/jir.2018.4

London, S. (2016). *Age and gender-based differences in self-efficacy and motivation in online Students.* (Ph.D. Dissertation). Grand Canyon University,

Malinovski, T., Vasileva, M., Vasileva-Stojanovska, T., & Trajkovik, V. (2014). Considering high school students' experience in asynchronous and synchronous distance learning environments: QoE prediction model. *The International Review of Research in Open and Distance Learning, 15*(91–122).

Martin, F., Tutty, J. I., & Su, Y. (2010). Influence of learning management systems self-efficacy on e-learning performance. *i-manager's Journal on School Educational Technology, 5*(3), 26–35.

McFarland, J., Hussar, B., de Brey, C., Snyder, T., Wang, X., Wilkinson-Flicker, S., . . . Hinz, S. (2017). *The condition of education 2017 (NCES 2017144)*. Retrieved from https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2017144

Means, B., Toyama, Y., Murphy, R. F., & Baki, M. (2013). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. *Teachers College Record, 115*(3). Retrieved from http://www.tcrecord.org/library/Issue.asp?volyear=2013&number=3&volume=115

Meyer, K. A. (2014). Student engagement in online learning: What works and why. *ASHE Higher Education Report, 40*(6), 1–114. doi:10.1002/aehe.20018

Miltiadou, M., & Yu, C. H. (2000). *Validation of the online technologies self-efficacy scale (OTSES)*. Paper presented at the Proceedings of SITE 2000, Society of Information Technology & Teacher Education Conference, San Diego, CA. ERIC, ED 445672

Nagel, L., Blignaut, A. S., & Cronjé, J. C. (2009). Read-only participants: a case for student communication in online classes. *Interactive Learning Environments, 17*(1), 37–51. doi:10.1080/10494820701501028

Nevid, J. S. (2009). *Psychology: Concepts and applications* (3rd ed.). Boston, MA: Houghton Mifflin Company.

Page, K., DK, & Mapstone, M. (2010). How does the web make youth feel? Exploring the positive digital native rhetoric. *Journal of Marketing Management, 26*(13–14), 1345–1366. doi:10.1080/0267257X.2010.523709

Pearson's product-moment correlation. (2018). Retrieved from https://statistics.laerd.com/premium/spss/pc/pearsoncorrelation-in-spss.php

Pellas, N. (2014). The influence of computer self-efficacy, metacognitive self-regulation and self-esteem on student engagement in online learning programs: Evidence from the virtual world of Second Life. *Computers in Human Behavior, 35*, 157–170. doi:10.1016/j.chb.2014.02.048

Prensky, M. (2001). Digital natives, digital immigrants part 1. *On the Horizon, 9*(5), 1–6. doi:10.1108/10748120110424816.

Prensky, M. (2001b). Digital natives, digital immigrants, Part II: Do they really think differently. *On the Horizon, 9*(6), 1–9.

Prensky, M. (2012). *From digital natives to digital wisdom: Hopeful essays for 21st century learning*. Thousand Oaks, CA: Corwin.

Prior, D. D., Mazanov, J., Meacheam, D., Heaslip, G., & Hanson, J. (2016). Attitude, digital literacy and self-efficacy: Flow-on effects for online learning behavior. *Internet and Higher Education, 29*, 91–97.

Pukkaew, C. (2013). Assessment of the effectiveness of internet-based distance learning through the vclass e-education platform. *The International Review of Research in Open and Distance Learning*, *14*(4). Retrieved from http://www.irrodl.org/index.php/irrodl

Puzziferro, M. (2008). Online technologies self-efficacy and self-regulated learning as predictors of final grade and satisfaction in college-level online courses. *The American Journal of Distance Learning, 22*, 72–89. doi:10.1080/08923640802039024

Ripley, A. (2013). Training and developing “digital natives” should be at the heart of UK business. *Development and Learning in Organizations: An International Journal*, *27*(5), 4–6. doi:10.1108/DLO-07-2013-0049

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. doi:10.28945/166

Saleem, H., Beaudry, A., & Croteau, A.-M. (2011). Antecedents of computer self-efficacy: A study of the role of personality traits and gender. *Computers in Human Behavior, 27*, 1922–1936. doi:10.1016/j.chb.2011.04.017

Samruayruen, B., Enriquez, J., Natakuatoong, O., & Samruayruen, K. (2013). Self-regulated learning: A key of a successful learner in online learning environments in Thailand. *Journal of Educational Computing Research, 48*(1), 45–69.

Shao, Z., Wang, T., & Feng, Y. (2015). Impact of organizational culture and computer self-efficacy on knowledge sharing. *Industrial Management & Data Systems, 115*(4), 590–611. doi:10.1108/IMDS-12-2014-0377

Shen, D., Cho, M.-H., Tsai, C.-L., & Marra, R. (2013). Unpacking online learning experiences: Online learning self-efficacy and learning satisfaction. *The Internet and Higher Education, 19,* 10–17. doi:10.1016/j.iheduc.2013.04.001

So, H.-J., Choi, H., Lim, W. Y., & Xiong, Y. (2012). Little experience with ICT: Are they really the Net Generation student-teachers? *Computers & Education, 59*, 1234–1245. doi:doi:10.1016/j.compedu.2012.05.008

Spearman's correlation. (2018). Retrieved from https://statistics.laerd.com/premium/spss/sroc/spearmans-rank-order-correlation-in-spss-3.php

Tang, Y., & Tseng, H. (2013). Distance learners' self-efficacy and information literacy skills. *The Journal of Academic Librarianship*, *39*, 517–521. doi:10.1016/j.acalib.2013.08.008

Teo, T. (2016). Do digital natives differ by computer self-efficacy and experience? An empirical study. *Interactive Learning Environments, 24*(7), 1725–1739. doi:10.1080/10494820.2015.1041408

Thangarasu, S., & DePaul, S. V. (2014). Development and validation of teacher computer self-efficacy scale. *IOSR Journal of Humanities and Social Science*, *19*(1), 33–39. Retrieved from www.iosrjournals.org

Travers, S. (2016). Supporting online student retention in community colleges. *The Quarterly Review of Distance Education*, *17*(4), 49–61.

Vayre, E., & Vonthron, A.-M. (2017). Psychological engagement of students in distance and online learning: Effects of self-efficacy and psychosocial processes. *Journal of Educational Computing Research, 55*(2), 197–218. doi:10.1177/0735633116656849

Verčič, A. T., & Verčič, D. (2013). Digital natives and social media. *Public Relations Review, 39*, 600–602. doi:10.1016/j.pubrev.2013.08.008

Voyer, D., & Voyer, S. D. (2014). Gender differences in scholastic achievement: A meta-analysis. *Psychology Bulletin. Advance online publication, 140*(4), 1174–1204. doi:10.1037/a0036620

Wang, C.-H., Shannon, D. M., & Ross, M. E. (2013). Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education, 34*(4), 302–323. doi:10.1080/01587919.2013.835779

Wilson, K., & Narayan, A. (2016). Relationships among individual task selfefficacy, self-regulated learning strategy use and academic performance in a computer-supported collaborative learning environment. *Educational Psychology, 36*(2), 236–253. doi:10.1080/01443410.2014.926312

Xiao, J. (2014). Learner agency in language learning: The story of a distance learner of EFL in China. *Distance Education, 35*(1), 4–17. doi:10.1080/01587919.2014.891429

Yong, S.-T., & Gates, P. (2014). Born digital: Are they really digital natives? *International Journal of e-Education, e-Business, e-Management and-Learning, 4*(2), 102–105. doi:10.7763/IJEEEE.2014.V4.311

York, T. T., Gibson, C., & Rankin, S. (2015). Defining and measuring academic success. *Practical Assessment, Research & Evaluation, 20*(5), 1–20.

Zeb, S., & Nawaz, A. (2016). Impacts of self-efficacy on organizational commitment of academicians: A case of Gomal University, Dera Ismil Kan, Khyber Pakhtunkhwa, Pakistan. *Information and Knowledge Management, 6*(1), 36–42.

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology, 25*, 82–91. doi:10.1006/ceps.1999.1016

Zimmerman, W. A., & Kulikowich, J. M. (2016). Online learning self-efficacy in students with and without online learning experience. *The American Journal of Distance Learning, 30*(3), 180–191.

Appendix A: Computer User Self-efficacy Scale

Part 1:

Your name____

Your gender: M F Decline to state

Part 2:

Below you will find a number of statements concerning how you might feel about computers. Please indicate the strength of your agreement/disagreement with the statement using the 6-point scale shown below. Circle the number that most closely represents how much you agree or disagree with the statement. There are no *correct* responses.

1. I can always manage to solve difficult computer problems if I try hard enough.

   strongly disagree 1 2 3 4 5 6 strongly agree

2. If my computer is "acting-up," I can find a way to get what I want.

   strongly disagree 1 2 3 4 5 6 strongly agree

3. It is easy for me to accomplish my computer goals.

   strongly disagree 1 2 3 4 5 6 strongly agree

4. I am confident that I could deal efficiently with unexpected computer events.

   strongly disagree 1 2 3 4 5 6 strongly agree

5. I can solve most computer programs if I invest the necessary effort.

   strongly disagree 1 2 3 4 5 6 strongly agree

6. I can remain calm when facing computer difficulties because I can rely on my abilities.

   strongly disagree 1 2 3 4 5 6 strongly agree

7. When I am confronted with a computer problem, I can usually find several solutions.

   strongly disagree 1 2 3 4 5 6 strongly agree

8. I can usually handle whatever computer problem comes my way.

strongly disagree 1 2 3 4 5 6 strongly agree

9. Failing to do something on the computer makes me try harder.

strongly disagree 1 2 3 4 5 6 strongly agree

10. I am a self-reliant person when it comes to doing things on a computer.

strongly disagree 1 2 3 4 5 6 strongly agree

11. There are few things that I cannot do on a computer.

strongly disagree 1 2 3 4 5 6 strongly agree

12. I can persist and complete most any computer-related task.

strongly disagree 1 2 3 4 5 6 strongly agree

Part 3:

1. What type of technology do you normally use?

2. What type of computer problems do you normally experience?

3. With respect to computers, what do you feel your experience level is?

Appendix B: Student Solicitation Email

Dear [redacted] student,

My name is John Otte and [redacted]. I am working on my doctoral dissertation in education and I am looking at computer self-efficacy in online learning (that is, how confident the student is in their ability to accomplish computer-related tasks) and if higher levels of computer self-efficacy results in higher completion rates. I am seeking volunteers to answer a short survey on how you feel about computers and how you solve computer related problems. At the end of the semester I will contact your instructor to see if you "successfully completed the course." This is the language in my dissertation and refers to students who passed with a C or better. However, my analysis may require access to your final course grade. If I do require your final course grade, I will contact your instructor who will be responsible for providing that information. Only your instructor will have access to your name. She will give you a pseudonym of Student 1 etc.

This survey should take no more than 10–15 minutes of your time. Attached to this email is a consent form. Please read over it. However, you will notice that some of the dates are incorrect. For example, this survey will take place during the Spring 2019 and with late-start classes. Also, the survey will be open from March 25–April 12. If you choose to participate please open and read the attachment. When you are ready to begin the survey, use the link below:

https://cuportland.co1.qualtrics.com/jfe/form/SV_0q4sADWdij9PjMN

The first question on the survey is your acknowledgement that you are received the consent form and that you agree to participate in the study.

This research could potentially help college administrators, faculty, and developers in designing better online courses and I appreciate your time.

Best,
John Otte,

John R. Otte, Jr. MA

Appendix C: Student Consent Form

Research Study Title: Computer Self-efficacy, Digital Learner, and Completion Rates in the California Community College System
Principal Investigator: John Otte
Research Institution: West Valley College
Faculty Advisor: Donna Graham, Ph.D.

Purpose and what you will be doing:
The purpose of this survey is to examine if computer self-efficacy (CSE) influences course completion among online California community college students. CSE refers the capabilities and judgment of ones capability to use a computer. We expect approximately 55 volunteers. No one will be paid to be in the study. We will begin enrollment on Monday, March 22nd, 2019 and end enrollment on Sunday, March 31st, 2019.

All you are expected to do for this study is answer a survey of 12 questions on a scale from 1 to 6 and three questions about how confident you are with computer related tasks. Based on your response you will be assigned a computer self-efficacy scale. This scale will then be compared to whether or not you passed the course at the end of the winter intercession. This survey should take no more than 20–30 minutes of your time.

Risks:
There are no risks to participating in this study other than providing your information. However, We will protect your information. Any personal information you provide will be coded so it cannot be linked to you. Any name or identifying information you give will be kept securely via electronic encryption on your CANVAS page. When the principal investigator looks at the data, none of the data will have your name or identifying information. We will refer to your data with a code that only the principal investigator knows links to you. This way, your identifiable information will not be stored with the data. We will not identify you in any publication or report. Your information will be kept private at all times and then all study documents will be destroyed 3 years after we conclude this study.

Benefits:
Information you provide will help educators and researchers develop better online learning platforms. You could benefit this by will gaining a better appreciation of the importance of being confident in your ability to solve computer related tasks and how this might affect your success in this course.

Confidentiality:
This information will not be distributed to any other agency and will be kept private and confidential.

Right to Withdraw:
Your participation is greatly appreciated, but you are free at any point to choose not to engage with or stop the study. This study is not required and there is no penalty for not participating.

Contact Information:

Please make a copy of this consent form. If you have questions you can talk to or write the principal investigator, John Otte at [redacted]. If you want to talk with a participant advocate other than the investigator, you can write or call the director of our institutional review board, Dr. Ora Lee Branch (email branch@cu-portland.edu or call 503-493-6390).

Your Statement of Consent:

I have read the above information. I asked questions if I had them, and my questions were answered. I volunteer my consent for this study.

____

Participant Name Date

____

Participant Signature Date

____

Investigator Name Date

____

Investigator Signature Date

Investigator: John Otte; email: [redacted]
c/o: Professor Donna Graham, Ph.D.
Concordia University–Portland
2811 NE Holman Street
Portland, Oregon 97221

Appendix D: Statement of Original Work

The Concordia University Doctorate of Education Program is a collaborative community of scholar-practitioners, who seek to transform society by pursuing ethically-informed, rigorously-researched, inquiry-based projects that benefit professional, institutional, and local educational contexts. Each member of the community affirms throughout their program of study, adherence to the principles and standards outlined in the Concordia University Academic Integrity Policy. This policy states the following:

Statement of academic integrity.

> As a member of the Concordia University community, I will neither engage in fraudulent or unauthorized behaviors in the presentation and completion of my work, nor will I provide unauthorized assistance to others.

Explanations:

What does "fraudulent" mean?

> "Fraudulent" work is any material submitted for evaluation that is falsely or improperly presented as one's own. This includes, but is not limited to texts, graphics and other multi-media files appropriated from any source, including another individual, that are intentionally presented as all or part of a candidate's final work without full and complete documentation.

What is "unauthorized" assistance?

> "Unauthorized assistance" refers to any support candidates solicit in the completion of their work, that has not been either explicitly specified as appropriate by the instructor, or any assistance that is understood in the class context as inappropriate. This can include, but is not limited to:

- Use of unauthorized notes or another's work during an online test
- Use of unauthorized notes or personal assistance in an online exam setting
- Inappropriate collaboration in preparation and/or completion of a project
- Unauthorized solicitation of professional resources for the completion of the work.

Statement of Original Work (Continued)

I attest that:

1. I have read, understood, and complied with all aspects of the Concordia University–Portland Academic Integrity Policy during the development and writing of this dissertation.

2. Where information and/or materials from outside sources has been used in the production of this dissertation, all information and/or materials from outside sources has been properly referenced and all permissions required for use of the information and/or materials have been obtained, in accordance with research standards outlined in the *Publication Manual of The American Psychological Association*.

Digital Signature

John R. Otte, Jr.
Typed Signature

November 3, 2019
Date