8-25-2020

Does Anywhere + Anytime = Success? Mobile Learning, Engagement, and Student Success in Higher Education

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A dissertation completed in partial fulfillment

of the requirements of the degree of

Doctor of Philosophy Education in

Leadership in Higher Education

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Abstract

This study aims to understand the possible impact of mobile learning on engagement and student success in the online environment. The research questions ask what impacts mobile learning has on student engagement, measured with Self-Regulated Learning (SRL); what impact mobile learning has on the SRL constructs of environment structuring, task management, and time management; and what associations mobile learning might have with student success and persistence. One hundred sixty-two undergraduate online students participated in the study through the survey instrument, utilizing the Online Self-Regulated Learning Questionnaire (OSLQ). ANOVA results showed that lower levels of mobile learning use engaged in SRL less when compared to the highest level of mobile learning use (HSD = -4.581, p = .001, d =.719). The lowest level of mobile learning used the SRL construct of task management less than the highest level (HSD = -2.624, p=.000, d =.796), as did the moderate level of mobile use (HSD = -1.681, p = .040, d =.494). Additionally, the lowest level of mobile learning used the SRL time management construct less than the highest group of mobile learning use (HSD = -1.293, p = .026, d =.505). Crosstabs analysis indicated no association between levels of mobile learning and measures of student success. These findings have implications for the development of online pedagogy, mobile learning theory, online course design, and student support initiatives.

Keywords: mobile learning, Self-Regulated Learning, online education, engagement, student success

Dedications

This dissertation and the years of research it represents is dedicated to my daughters, Caroline and Sadie. May they always be curious and innovative learners.

Acknowledgments

First, I would like to thank my committee chair and advisor, Dr. Mike Vetter. His calm, steadfast guidance helped minimize the inevitable hiccups in the process and kept this on track. The expert statistics guidance of Dr. Grant Smith challenged me to think clearer and go a step further. And appreciation goes to the essential early guidance from Dr. Tony Piña for helping me narrow my research focus.

I am deeply grateful for the support of my family and friends throughout this journey. My husband, Drew, offered unwavering support, love, and comedic relief which was both renewing and sheltering. I am thankful for the patience and support of my daughters through this journey as well.

I am so proud and thankful to be a part of Cohort A. This is the most diverse and talented group I have had the privilege to be a part of in all my years in higher education.

I do not have enough space to acknowledge all the friends who gave essential support for my goals and this endeavor. I owe so much to the friends who kept me grounded, encouraged, and refreshed. I would specifically like to acknowledge the late Jeremy Lewis and Jeff Fuson who were two of my early encouragers who never doubted I would succeed. I saddened that they are not here to see the conclusion of this journey.

Chiefly, I give thanks to God, my guide, my ikigai. Through Him all is possible, and with Him all is endurable.

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Chapter 1

Higher education has experienced much change in the last two decades, and perhaps none with such transformative promise as online education. As online education has grown, so too has society's general acceptance and adoption of technology for all of life's needs and pursuits. These changes, along with increased quality, have helped to establish online education as a viable option for higher education. In the five years from 2012 to 2017, the portion of college students who took at least one class online had a net increase of 5% (Lederman, 2018b). As of Fall 2018, the most recent year for which data is available, 35.3% of all college students took online courses; of that group, 18.7% took at least one course online, and 16.6% took all their courses online and were enrolled in exclusively online programs (National Center for Education Statistics, 2019a). Research on the efficacy of online education is continuous and evolving as the technologies used for online education and learning evolve.

An early and continuous question for online learning is that of student success. Student engagement is often an undercurrent in the discussions of online student success, as engagement is a crucial element affecting many aspects of a student's success in the online environment such as retention, persistence, academic success, and satisfaction. Amid the growing research and improvements in online learning, low retention rates still plague online learning perhaps more than traditional learning (Allen et al., 2016; Bawa, 2016). Many researchers view this retention issue through the lens of student engagement and student success (Bawa, 2016; Baxter, 2012; Dietz-Uhler et al., 2008; Drouin, 2008; Fetzner, 2013; Finnegan et al., 2009; Fisher & Baird, 2005; Hartnet, 2012). A body of research on student success online has established groups of predictors used by institutions in predictive modeling to determine effective interventions (Boston & Ice, 2011; Fike & Fike, 2008; Finnegan et al., 2009; Hachey et al., 2012; Lee & Choi, 2013; Morris et al., 2005; Morris & Finnegan, 2009; Nichols, 2010; Park & Choi, 2009). The majority of the inquiry focuses on student characteristics or student engagement behavior in the online class without consideration for the method of access. As technology, in general, has become more mobile, educational technology has yet to harness the full potential of mobile educational technology. Accessing and taking part in online learning through a mobile device is termed mobile learning and is growing in consideration with higher education thought leaders. Joshua Kim, one of many who regularly report on higher education and technology, has echoed the calls for higher education at large to fully embrace mobile learning, claiming that mobile learning is the future for higher education whether institutions want it or not (2016a, 2016b).

Pew Research (2019) notes that now 81% of American adults own a smartphone, with 94% of adults aged 18-29 owning a smartphone and 92% of adults aged 30-49 owning a smartphone. Overall, smartphone ownership has risen four percentage points since 2018, and the percentage of adults aged 30-49 who own a smartphone rose three percentage points over the same period (Pew Research, 2019). Tablet ownership has also been on the rise and is currently captures 53% of American adults (Pew Research, 2019). Additionally, the Pew Research Center has tracked the percentage of Americans who are “smartphone dependent,” meaning they do not have highspeed broadband internet service at home, opting instead to depend on their smartphones for internet access. Since 2016, the rate of smartphone dependent adults has risen from 12% to 20%, with 28% of 18-29-year-olds being smartphone dependent (Pew Research, 2019). The EDUCAUSE Center for Analysis and Research (ECAR) study of student technology use found that students spent an average of 1-4 hours per day of online time studying or doing homework (Galanek et al., 2018). Students who spent more time online reported spending 3-5 or more hours online studying or doing homework per day compared to other activities online, such as social media or video streaming (Galanek et al., 2018). A 2015 national study of students in grades 4-12 uncovered telling preferences for up and coming college students (Pearson, 2015). A summary of the report shows young students' desire for mobile device supported learning. The two findings most relevant to higher education are that a majority of the students felt that tablets were a “game-changer” for education and that tablets and 2-in-1 devices, portable computers with features of a laptop and a tablet, were most desired for their future education (Pearson, 2015). Starting in Fall 2020, the 8th graders in that study will be enrolling in our institutions with the expectation of mobile supported learning. With the majority of students attending college with one or more mobile devices plus the continued popularity of online courses, it will only be natural for these digitally-enabled students to be inclined to use their mobile devices for online learning.

This study aims to understand the impact, if any, that mobile learning has on students' engagement and academic success. For the purposes of this study, academic success is defined as a combination of grade performance and completion. Student engagement is defined as the effort students dedicate to their educational pursuits to achieve desired outcomes. Knowing the potential effects mobile learning has generates implications for online course design, online pedagogy, student access, and student success.

Problem statement

Student enrollment in online courses has been increasing over the past decade (Allen et al., 2016; Aslanian & Clinefelter, 2016, 2017; Ginder et al., 2017). At the same time, online education as a whole has not been able to maintain strong retention or persistence rates. Drop out rates vary among institutions, but nationally reports of online student attrition are 40% to 80% (Bawa, 2016; Lederman, 2018a), whereas nationally, attrition rates for traditional education have remained steady at approximately 25-30% (National Center for Education Statistics, 2019b). This is a consequential problem plaguing online education that can be addressed through increasing student engagement and student success.

The number of current students reporting using mobile devices to access online coursework (i.e., individual courses) and complete some work is increasing – 40% in 2016, 67% in 2017, to 70% in 2018 (Aslanian & Clinefelter, 2016, 2017; Magda & Aslanian, 2018). Additionally, 66% of prospective online students would like to complete at least some of their individual coursework through a mobile device (Clinefelter et al., 2019). These two findings indicate that current students are using their mobile devices at least some of the time to support their learning and that a majority of prospective students are planning to do the same. However, the research surrounding mobile access and student success are scant. Current research on success in online education does not factor in mode of access, and primarily focuses on retention as a measure of success. Retention is an incomplete measure of academic success since it does not consider grade performance, course engagement, or any other combination that encourages students to stay in a course (Puzzziferro, 2008). Research addressing dropout and attrition rates does not often consider the behaviors that indicate engagement or lead to academic success. Since it is well established that engagement is important to online learning (Hu & Ku, 2001; Martin & Bolliger, 2018; Robinson & Hullinger, 2008) and can have an impact on a student's academic success, more research is needed to investigate the effect new technologies, such as mobile devices, have on engagement and success.

Purpose

The purpose of this study is to address the lack of research on mobile learning and its impact on student engagement and academic success in online education. As more online students incorporate mobile learning into their available options to support their academic success, more understanding of how students are using this tool and its potential impact on engagement is needed. The online environment requires a higher level of engagement, self-discipline, and determination to be successful, and the "anywhere, anytime" nature of mobile learning demands even more. Self-Regulated Learning theory (SRL) provides a compatible lens from which to view the environment of engagement with mobile learning.

Research Questions/Hypothesis

RQ1: What impact does mobile learning have on student engagement in an online class?

H_1: Mobile learning has a positive impact on student engagement in an online class.

RQ2: What is the extent of the impact of mobile learning on Self-Regulated Learning constructs?

H_2: Mobile learning has a significant impact on the Self-Regulated Learning constructs of environmental structuring, task strategies, and time management.

RQ3: How does student engagement, measured through Self-Regulated Learning, affect student success online?

H_3: Student engagement has a positive impact on student success online

Significance of the Study

The world is becoming increasingly mobile and less formal, and higher education is not immune to this. Traditional boundaries between school, work, and life are changing, if not disappearing. Beyond helping students optimize their mobile device usage, this study has implications for online pedagogy, online course design, and student preparedness. Online pedagogy is still a developing theory, and understanding more about which student behaviors have a beneficial impact on online course success should help shape teaching methods and theory. New tools are being developed to enhance the online classroom experience. Understanding how students utilize their mobile devices to engage in their learning can help course designers choose appropriate tools and design features to make courses more mobile friendly and engaging for students. As researchers continue to learn more about what factors and behaviors foster student success, these strategies for success can be disseminated to students through orientation programs and built into academic support services.

Conceptual Framework

This study exists in the space where models of online retention and persistence overlap with mobile learning and SRL models. Success in online education is an amalgam encompassing tools students use for online learning, the flexibility afforded by online learning and mobile learning, and the regulatory, self-aware behaviors students engage in during learning. The conceptual framework used in this study is comprised of mobile learning, SRL, and student engagement.

Mobile learning is defined as situationally based on the mobility of learners and learning contexts, allowing for fluidity of personal learning in time, content, and context, and mediated through technology (El-Hussein & Cronje, 2010; Sharples et al., 2016). Mobile learning as a theory complements other theories of student success online while covering the gaps of contextuality and fluidity of learning and technology. As a practice, mobile learning fills the gaps for students who desire the ability to study and engage in their courses whenever and wherever they can. While online learning requires a particular type of self-discipline for success, mobile learning adds an extra level of self-regulation due to the anytime, anywhere possibility for learning and success.

SRL is defined as "the self-directed process through which learners transform their mental abilities into task-related academic skills. This approach views learning as an activity that students do for themselves in a proactive way" (Zimmerman, 2001, p. 1). Pintrich (2004) defined four assumptions of SRL in the higher education context: the active, constructive assumption; the potential for control assumption; the goal, criterion, or standard assumption; and the mediation between personal and contextual characteristics and actual achievement or performance. The two most relevant assumptions for mobile learning are the potential for control assumption and the assumption that SRL activities are "mediators between personal and contextual characteristics and actual achievement or performance" (Pintrich, 2004, p.388). One common attraction of online learning for the various students who choose such a learning environment is the ability to better control when and how often they engage in the course (Puzziferro, 2008). It is assumed that self-regulated learners intentionally exercise such control over their learning activities. All college students must mediate themselves in their learning environment, such as relying on certain learning strategies in the classroom. However, online students engage in this mediation between the self and the environment on different levels and with more fluidity. While the online course environment may stay the same within that one course, the context and environment for learning will also include the location of the student such as home, work, or a coffee shop, and all the variable contexts each environment brings. Through the lens of SRL, students would structure these environments and mediate themselves as best as possible to positively impact their performance or academic achievement. Through SRL activities, mobile learners can structure their fluid contexts to best meet their needs. Thus, increased and targeted activities in an online class through mobile access can create the best environment for achievement or success.

Student engagement has had numerous applications and definitions in the literature. These definitions fall into two general groups, those which consider institutional involvement and those which only consider students' behavior and thinking (Trowler, 2010). This research is focused on students' behavior, so Hu and Kuh's (2001) definition of student engagement is the most operable. Hu and Kuh define student engagement as "the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes" (2001, p.3). Students practicing SRL will also be more engaged learners as a by-product of their self-regulation efforts.

Summary of Methodology

The population of interest is undergraduate students at one mid-sized university taking fully online courses. The sample university structures online studies by 8-week bi-term courses in one 16-week semester, and students may take one to three courses in one bi-term. Potential participants, then, may be enrolled part-time or full-time, and with an age range of 18-66 years.

Convenience sampling was used for the study population (n=1,641). All actively enrolled online students had the opportunity to participate in the study by choosing to complete the survey. The sample was stratified by levels of mobile learning use, as determined by the survey instrument. The survey instrument was the Adapted OSLQ (Online Self-Regulated Learning Questionnaire). The OSLQ was adapted from the work on conceptualizing SRL by Zimmerman (2008). The short-form of the OSLQ was used because it contains six constructs of self-regulation in the online environment: environment structuring, goal-setting, time management, help-seeking, task strategies, and self-evaluation (Barnard et al., 2008).

Limitations

One limitation of the study is the self-reported data collected by the survey. Self-reported data may not be accurate. Thus, students may misjudge their levels of engagement with SRL behaviors (Schraw, 2010). A second limitation is that the results of the study may not be generalizable beyond the type of course the participants of the study were enrolled in.

A third limitation is the convenience sampling used. Convenience sampling does not provide a random sample. It introduces non-response bias, meaning that the sample may not be representative of the population and may have missed selecting students with varying levels of engagement or success (Bethlehem, 2010).

The survey was administered at the completion of one academic term and the beginning of another. This is the fourth limitation as it may have eliminated students from the sample who did engage in mobile learning but were not successful in the course. Thus, they may have been demotivated to take the survey, which would affect having a representative sample and an equal distribution of final course grades.

Term definition

Key terminology used in the study is defined below.

Mobile Learning - Accessing and taking part in online learning through a mobile device

Mobile Device - a tablet or smartphone with internet capabilities

Online Learning– at least 80% of the class content is delivered exclusively online

Student Engagement - "the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes" (Hu & Kuh, 2001, p.3)

Student Success – a combination of grade performance, completion, and persistence (Puzziferro, 2008)

Persistence – students who continually enroll from term to term, focused on the course level, often measured with full-time and part-time enrollment

Retention – students maintaining continuous enrollment culminating in graduation, often measured by full-time enrollment

Summary

The popularity and quality of online classes have been increasing in higher education, and, as technology becomes more mobile in general, students will use their mobile devices to engage in their online classes at least some of the time. The online learning environment requires more self-discipline and regulation for success. As such, the theory of SRL is an applicable lens through which to measure behaviors that impact student success in the online class. The purpose of the study is to measure the effect mobile learning has on student engagement and academic success in online education. The results illuminated by this study can influence online pedagogy and course design.

Chapter 2

Online learning is distinct from the traditional environmental context of higher education. Online students may be connected to a campus, taking a mixture of online courses and traditional face to face courses. However, many online students take classes through universities they may never visit. While online students can create meaningful connections with faculty and peers, their access to support services is often vague or absent (Kim et al., 2016), which can create a possible disconnection from campus. Higher education students in the online learning environment need to be more disciplined, self-starting, and organized. Past theories of student motivation and engagement, such as Astin's seminal 1999 work, are not fully applicable to the online learning environment and mobile learning (Zimmerman, 2008), as on-campus and in-classroom experiences are components of the theories. Teaching techniques centered on a classroom setting do not always translate to the online environment.

Additionally, since mobile learning is presumed to occur in settings beyond the university or any place that resembles a learning environment, theories that consider these environmental factors and how that might affect student behavior are needed. More pertinent theories of learning, academic support, and student services in the online environment are necessary to address the lower retention rates for online students and to integrate the trends and development of technologies that facilitate online learning, such as mobile learning. Approaching mobile learning with a developed theory of learning will deepen our understanding of the learning that is possible in this dynamic environment, and this will be a significant step forward for increasing student success online.

The following review will first explore theories of online retention and persistence and predictive models that have tested those theories. That investigation leads to the topic of engagement, which is defined, and literature pertaining to its application for the online environment is explored. Student Success theory is then addressed and defined for the online learning context. Next, the emerging theory of mobile learning is examined as well as the noteworthy research models being applied to mobile learning. Finally, Self-Regulated Learning theory (SRL) and modeling are surveyed as a unifying approach to the theories underpinning this research.

Retention and persistence

Retention and persistence are often used interchangeably in the literature. Discussions on the delineation between these terms are varied in meaning and importance, even more so when applied to on-campus students or online students. However, several national data collection services and accrediting bodies are beginning to note the difference and significance. According to Noel-Levitz, retention is a yearly measure of students enrolled from one fall term to the next fall term, and persistence is a more fine-tuned measure of the enrollment of students between terms, such as from fall to spring semesters; completion is an even more specified measure of how many students who started a course finished the course (Voigt & Hundrieser, 2008). For institutions that offer regular, year-round terms or continuous enrollment, such as community colleges, persistence rates are just as important as retention rates. Administrators focused on improving retention rates will often drill down to the persistence rates of programs, courses, and students to catch students before they fall away. In the online learning environment, this is of particular concern.

The research on retention and persistence in online education is varied. Much of the research focuses on factors affecting retention or persistence with researchers concentrating on factors such as previous experience with online courses, transfer credits, GPA, students’ level of support, student support services, and course satisfaction (Boston & Ice, 2011; Fike & Fike, 2008; Hachey et al., 2012; Nichols, 2010; Park & Choi, 2009). For the purposes of this study, research on student behaviors will be a focus as they can be more closely tied to individual student engagement and success.

Predictive modeling is one focus of the literature on online student retention. Early researchers investigating the predictive power of online retention models were Morris, Wu, and Finnegan (2005). Using data from 2002 of general education students, Morris, et al. (2005) found that internal locus of control and financial aid predicted 75% of students group membership as completers or non-completers. Locus of control refers to a student's belief about the degree of control (internal or external) over one's environment or happenings. Morris and Finnegan (2009) also noted the importance of locus of control on academic achievement. Online students with a high internal locus of control had greater academic achievement (course level) compared to students with low internal locus of control (Morris & Finnegan, 2009). Additionally, Morris and Finnegan (2009) found that completers, students who maintained continuous enrollment through a course, engaged in learning behaviors in the online course with more frequency than non-completers and completers' time-on-task was significant to their persistence in the course.

Next, Finnegan, Morris, and Lee (2009) investigated if course discipline was a significant factor in student behavior, achievement, and persistence in online courses. Among the results, the study found that students who completed the course spent more time on discussion boards and course content on each visit and did so with more frequency than non-completers (Finnegan et al., 2009). In this study, students with more experience with the online environment seemed to know what behaviors would benefit them the most in terms of grade points or percentage (Finnegan et al., 2009). This last finding was similar to Hachey, Wladis, and Conway (2012).

Student satisfaction and sense of community in the online environment may also be a significant factor for retention or persistence. To test this, Drouin (2008) investigated the within-course effects of students' sense of community, satisfaction, and achievement and found that students' sense of community was significantly related to the available interaction methods in the course. Students who had higher frequency of student to student, student to instructor, and student to content interactions had a greater sense of community and satisfaction (Drouin, 2008). However, sense of community and satisfaction was not significantly related to achievement (Drouin, 2008).

In the literature on retention, locus of control is a recurring theme. The possible effect of academic internal locus of control on flow was tested by Lee and Choi (2013), as well as course satisfaction and use of learning strategies in online courses. Results of the structural equation modeling showed that students' academic locus of control had the greatest effect on the other factors and on student retention, and the use of learning strategies had the second most significant effect on student satisfaction (Lee & Choi, 2013). Though this study was intriguing for its inclusion of learning strategies, the research was not specific on what strategies were employed.

Among the literature on factors that impact online retention or persistence, student behavioral factors of locus of control, time-on-task, and frequency of interactions have been shown to make a difference. This literature edges closer to the theme of engagement in online classes, as behaviors such as spending more time on assignments and having an internal locus of control may be manifestations of student engagement in the course. A common motivation for this research on retention and persistence is the overall impact on students' academic success online, and the belief that these types of student behaviors can be influenced or changed to increase students' chances of success.

Engagement

The belief that student behaviors can be influenced or changed to positively impact their success is the foundation for any discussion on student engagement. The term student engagement is used widely in the literature for a myriad of topics, as engagement itself is relevant to multiple avenues of higher education. This discussion of engagement will attempt to focus on the online education context.

Hu and Ku begin their 2002 seminal work on engagement and disengagement by asserting that "the most important factor in student learning and personal development during college is student engagement, or the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes" (p.555). While this work focused on the traditional on-campus setting, this definition holds fast across all settings of higher education. Adding to this proclamation is Trowler's (2010) in-depth analysis of engagement theory, application, and policy in higher education. Based on this analysis, engagement is said to have three primary dimensions: behavioral engagement, emotional engagement, and cognitive engagement (2010).

While a considerable amount of research exists on engagement, much of it centers on traditional, face-to-face contexts of education. Dumford & Miller (2018) take note of this as well as a motivating rationale for their research on engagement of students who access their online learning at varying levels. Using NSSE data (National Survey of Student Engagement), engagement measures were compared by first-year students and Seniors. For first-year students, the greater amount of online classes they took had a positive effect on the amount of time they gave to quantitative reasoning, and more online courses were overall related to more engagement (2018). For seniors in the study, quantitative reasoning decreased as did many of the other measures of engagement as the number of online classes taken increased (2018). These findings might suggest that the online environment itself requires certain types of engagement, but that there may be a tipping point where the demand from several online classes causes students to disengage. It is noteworthy though that the NSSE does not measure self-directed engagement behaviors like methods online students take to manage or adapt their study needs or frequency of engagement with online study.

In another approach to testing engagement in the online environment Benson (2020) explains the redesign of an online nursing course. The redesign was undertaken to address student frustration and signs of disengagement with the course. The project proved that course design for engagement, rather than exclusively for content delivery, had positive results for engagement, satisfaction, and success (2020). The course redesign focused on course structure, course management, and instructor-student interaction so that students had more apparent learning objectives, more opportunities for feedback, and a higher quality of instructor-student communications (2020). These findings are congruent to those of Finnegan et al. (2009) and Drouin (2008), although their studies concerning course design and course features were focused on the retention effects.

Much of the literature on engagement is qualitative, which keeps the level of information available on engagement broad and more generalized. Conversely, Farrell & Brunton (2020) provide a valuable case-based investigation of engagement behaviors in an online class. Their case study of 24 sociology students described five key findings that highlight the three primary dimensions of engagement (behavioral, emotional, and cognitive). The five themes from the analysis were peer community and support, tutor support to reinforce learning, studying while balancing life, confidence, and personal approaches to learning (2020). Time management was a prominent topic within the theme of studying while balancing life as students expressed their efforts to structure time to study and creating personal study schedules. Farrell & Brunton's findings also provide many details from participants about their individualized and innovative study techniques. These students seemed to inherently know the efforts needed to stay engaged in the class and the benefits of that engagement.

Students' academic success is at the center of each of these methods of inquiry. Many factors can affect student success in the online environment, but engagement had a broad agreement about its importance and connection with student success in any educational environment (Dumford & Miller, 2020; Hu & Kuh, 2002; Towler, 2010).

Student success

Student success is a central focus of a great body of research on higher education in general and in the online environment. Institutional functionality, program design, course design, academic services, student retention, student persistence, and much more are all used as indicators or influencers of student success. Definitions of student success vary widely depending on the context, such as institutional effectiveness versus program effectiveness. On academic and student levels, student success is conceptualized as consisting of three categories: grade performance, completion, and satisfaction (Puzziferro, 2008). Studying any one of these categories individually can be misleading.

Additionally, student characteristics used in place of any of these, such as students' high school performance, SAT or ACT scores can be equivocal. A trend in researchers testing predictors of student success is often to use just a GPA score, but such an isolated scope can result in an incomplete understanding. Similarly, focusing just on completion would leave out possibly important academic achievement information, since successful students also leave (transfer, stop-out or pause-out). Student satisfaction is typically a self-reported measure and thus is too subjective on its own for determining student success. Thus, the better approaches to student success include measures from more than one of the categories to provide a more whole concept of student success.

Mobile Learning

Over the last decade, as online education itself has grown and found a common place among all types of higher education institutions, mobile learning has arrived with greater speed. Instead of a rapid arrival to overtake online education's space, mobile learning is overlapping and filling in gaps to increase online education's potential impact. "The purpose of higher education and the relatively new ubiquity of mobile devices in our culture have imbued the mobile device with new meanings. Higher education can now be presented in a more sustained and interactive fashion to empower those who need it" (El-Hussein & Cronje, 2010, p. 15).

In the literature, the terms "m-learning", "mLearning", and "mobile learning" are used interchangeably. Mobile learning will be used throughout this research for clarity. As the research and applications of mobile learning have increased over the years, various definitions of mobile learning have attempted to rise to the surface. One commonality and dual influence on these early definitions was the metamorphic technology used for mobile learning. Many early researchers took care to stress that the technology employed is not mobile learning in itself, but a method of access. El-Hussein and Cronje (2010) and Sharples, Taylor, and Vavoula (2016) work through these early definitions to establish the concepts central to mobile learning. A theory of mobile learning must be significantly different from other theories of learning situated in physical environments; it must encompass formal, informal, and non-formal learning; it must theorize learning as a constructive and social process; and it must analyze learning as personal, contextual, and mediated by technology (Sharpels et al., 2016).

These assertions about mobile learning can be brought together in this definition: mobile learning is situationally based on the mobility of learners and learning contexts, allowing for fluidity of personal learning in time, content, and context, and mediated through technology (El-Hussein & Cronje, 2010; Sharples et al., 2016).

The mobility of modern technologies creates the environment for learners to access educational content beyond the traditional bounds of higher education. Martin, McGill & Sudweeks (2013) open with this concept stating "[Mobile learning] transcends the barriers between in-class and out-of-class experiences with opportunities for anywhere anytime learning and the potential for students to participate in educational activities beyond the limitations of traditional study environments" (p. 51). An often-used term that is tangential to "mobile" is "ubiquitous," referring to the anywhere, anytime nature of mobile technology making mobile learning possible "when needed" and "just in time" (Al-Emran, et al., 2016; Pimmer et al., 2016; Sha et al., 2011). These characteristics of mobile learning make it a cogent instrument for delivering and reinforcing content with students that would customarily only be available behind the perceived barriers of traditional higher education (El-Hussein & Cronje, 2010).

Research investigating and applying mobile learning has progressed along two main channels: mobile learning as support to traditional learning and mobile learning as the mediator of learning. When researchers began to recognize the potential for mobile learning, it was utilized as a support for traditional classroom learning. 2010 became a notable year for mobile technologies and its researchers, for this was when tablet popularity boomed, and researchers were eager to test its educational possibilities. A notable focus in research on mobile learning after 2010 focused on student readiness or student motivators and behaviors for learning in the mobile environment (Cheon et al., 2012; Martin et al., 2013; Vilkonis et al., 2013).

Students' potential to use mobile learning products was tested by Chinese researchers finding that near-term usefulness, long-term usefulness, and personal innovativeness were significant factors for students' willingness to try mobile learning (Liu et al., 2010). However, these students only reported on their willingness to use mobile learning, not on their actual use of such technologies. iPad use in the college classroom compared to laptop use was studied with a group of undergraduate students with mixed results for perceived learning versus perceived engagement; however, students reported that the iPads allowed for greater capacity for collaborative work than laptops did (Rossing et al., 2012). In both studies, students showed heightened interest and intention in mobile learning but held some frustrations with learning to use the technology, and both studies still only conceptualized the learning experience as tied to the specific classroom context (Liu et al., 2010; Rossing et al., 2012). The research of Martin, McGill, and Sudweeks (2013) provided encouraging support for students' use of mobile learning, noting that a significant majority of students agreed when asked if mobile learning motivated students to be engaged. Still, this study involved students in traditional educational contexts. One study surveyed in more depth American students' attitudes about learning with cellphones and smartphones. The advantages of using mobile learning were the predominant theme amongst these students (Gikas & Grant, 2013). Attention on mobile learning began to fully recognize the informal learning possibilities afforded by mobile learning in the last few years, though exploration of this element of the theory was still primarily classroom-focused in 2016 (Khaddage et al., 2016). Cultural factors (i.e., developing technological infrastructure) may be a compelling force for holding mobile learning on campuses (Liu et al., 2010; Vázquez-Cano, 2014).

Among these studies, common motivating factors or benefits of mobile learning expressed by students were quick and easy access to information, course content, and learning resources; the ability to upload content; participating in discussion boards; and the immediacy of contact between students and with faculty (Gikas, & Grant, 2013; Martin et al., 2013; Vázquez-Cano, 2014).

The transition from mobile learning as support to mobile learning as a mediator of learning signifies a conceptual change of how one views mobile learning. Such a shift influences the applicability and development for mobile learning within institutions and the wider higher educational landscape. Mobile learning is most compatible as a subset of e-learning, encapsulating the best practices of learning design through the online environment; after all, education is essentially communication, and mobile learning is a new avenue for communication. Indeed, the greatest barrier to mobile learning moving beyond the bounds of the classroom may be a lack of imagination and innovative institutional policies (Rajasingham, 2011). The development of learning analytics and what it can show of students' anytime, anywhere engagement is evidence of this conceptual change. Learning analytics has been tested as not just a tracking tool, but a self-reflective and regulatory tool for learners (Tabuenca et al., 2015). When teachers' estimates of time for a task were compared with students' time-logs for the task, Tabuenca, et al. (2015) found that students' time management showed significant improvement by being aware of how much time they were or were not spending on learning activities occurring through mobile learning.

As some cultures made the leap from minimal personal computer ownership to majority cellphone and smartphone ownership, higher education leaders were quick to realize the possible impacts of mobile learning to reach populations previously excluded from higher education due to distance or economic status (Vilkonis et al., 2013). In this context, students often note mobile learning's usefulness and their willingness to engage with it, and in some cases, educators believe in its usefulness even more (Al-Emran, et al., 2016). The generative work of Sharples et al. (2016) encompasses this view of mobile learning and allows for greater imagination for its uses and applications. When a mobile SRL platform was developed for English Language learners, Zheng, Xin, and Chen (2018) found that students who used the system had significantly higher learning gains than students who did not use the system.

Self-Regulated Learning

Online education and mobile learning require successful students to be more disciplined and intentional about their learning because of the multifaceted evolving nature of the online environment. The theory of Self-Regulated Learning (SRL) was first developed for the primary and secondary education levels and focused on understanding the cognitive, motivational and behavioral skills of students and how that might enable them to be masters of their learning (Zimmerman, 2001). Zimmerman (2001) defines the theory as "neither a mental ability nor an academic performance skill, self-regulation refers instead to the self-directed process through which learners transform their mental abilities into task-related academic skills. This approach views learning as an activity that students do for themselves in a proactive way" (p. 1). SRL encompasses three general types of strategies: cognitive learning strategies, self-regulatory strategies to control cognition, and resource management strategies (Pintrich, 2004, 1999; Zimmerman, 2008, 2001). The theory was then applied to the higher education environment, developing an SRL framework for college students (Pintrich, 2004). In his framework, Pintrich identifies four assumptions of SRL common among SLR models. The two assumptions most relevant to online learning and mobile learning are the potential for control assumption and the assumption that SRL activities are “mediators between personal and contextual characteristics and actual achievement or performance” (Pintrich, 2004, p.388). This indicates that through an SRL lens, some regulation of cognition, motivation, and behavior is possible and that students could mediate the interaction between personal characteristics, environmental contexts, and their academic achievement. For example, working adult students often choose online education over the traditional context for their higher education because of the perception that it is their best chance to regulate their time and abilities with the learning environment.

Pintrich (2004) further notes how the elements of SRL become phases that college students continually move through: planning and goal setting; monitoring processes; efforts to control or regulate the self, tasks, or context; and reaction and reflection. Among the categories of SRL, regulation of behavior is of utmost interest to the current study. Regulation of behavior is a category that encompasses students' attempts to control their manifest behavior. Behaviors that are relevant to academic environments are planning and management of time and effort as well as help-seeking behaviors (Pintrich, 2004). Effort planning refers to a student’s attempts to judge the activity and labor involved in a task and plan for how to complete it. In these ways, SRL has a natural connection with mobile learning because of the self-determined and self-regulated nature of the anytime-anywhere environment of mobile learning.

Since Pintrich’s (2004) initial application of SRL to higher education, researchers frequently test the applicability of the theory to the online environments. Because of the opaque nature of online learning, SRL presents a lens to highlight the measurable qualities of student’s learning efforts online. Time management and effort regulation are two common measurable behaviors that researchers use in testing the effects of SRL. A significant study on SRL and all online students surveyed a wide range of community college students, finding that study environment, time management, and effort regulation were all significant to these students for their academic performance (Puzziferro, 2008). The results of Puzziferro's study suggest that students who received higher final course grades were more likely to manage their study time (the planning, scheduling, and execution of it) and their study environment, further suggesting that these students could more effectively match their study habits to their study style. Similar results were found for effort regulation and course grade (Puzziferro, 2008). Effort regulation refers to a student's ability to manage tasks and commitment to the task, especially in the face of distractions or obstacles. This research with online community college students drew clear connections between the SRL behaviors of effort regulation, time management, and study environment and the student's final course grades.

Student's intrinsic goal orientation and academic self-efficacy have been studied with the SRL strategies of effort regulation, metacognitive regulation, and interaction regulation. Intrinsic goal orientation and academic self-efficacy were positively associated with and mediated by effort regulation, metacognitive regulation, and interaction regulation (Cho & Shen, 2013). Interaction regulation refers to communication interactions between students and between student and teacher. The total amount of time students spent in the LMS (Blackboard) plus their effort regulation together were significant predictors of course grade (Cho & Shen, 2013). The more time (in total) students spent on Blackboard and the greater they regulated their efforts for the course, the greater their academic achievement at the conclusion of the course.

Broadbent and Poon's (2015) systematic review of the literature on SRL strategies and academic achievement brought to light several categories of SRL that proved significant in the online learning environment. Among the 12 studies included in the analysis, the SRL categories of time management, effort regulation, metacognition, and critical thinking had positive correlations with academic achievement (Broadbent & Poon, 2015). Despite this limited body of research, these categories continued to show evidence of positively impacting students' academic success in the online environment.

A follow up to this study compared fully online and blended learners' SRL strategies and academic success. For both groups, time management, elaboration, and effort regulation were the most used SRL strategies by both groups (Broadbent, 2017). For fully online learners, the use of elaboration, organization, metacognition, time management, and effort management were significantly higher than for blended learners; Peer learning and help-seeking strategies occurred at a higher rate for blended learners (Broadbent, 2017). These results suggest that the online environment requires students to implement time management and effort regulation more than other learning environments and contexts. Additionally, Broadbent's (2017) study found that only effort regulation and time management positively predicted course grade for online students.

Some efforts to create more long-term applications of mobile learning have centered on embedding mobile learning activities in previously traditional learning contexts such as making lectures more interactive, fostering collaboration with on-campus students, and creating archivable learning materials such as podcasts (Dyson et al. , 2009). For one such application, researchers first developed a mobile context-aware GPS program for English language learners in Taiwan to learn different plants growing on campus (Sun et al., 2015). The researchers then applied self-efficacy and self-regulation to the students’ uses of and learning through the program. Both self-efficacy and self-regulation were significant predictors of academic achievement for both high and low achieving groups (Sun et al., 2015). These findings suggest that SRL is a beneficial strategy for all student skill levels.

Limited research exists testing the impact of SRL in the mobile learning environment. Though research on mobile learning has increased in the past few years, much of the theory application has been with behavior theories such as Technology Acceptance Model and Theory of Planned Behavior. Sha, Looi, Chen, and Zhang (2011) note the sparse theory development for mobile learning and SRL across different fields. As the previous analysis has shown, much of the theory development to date has stayed centered in the online learning environment, but not specifically mobile learning. Nevertheless, Sha et al. (2011) state, “mobile learning environments presumably provide a means by which students can exercise agency to control their own [behavior] and cognition” (p. 367). SRL is an applicable theory, according to Sha et al. (2011), because “knowledge and skills of SRL can be seen as a precursor to mobile learning, as well as one of the desired outcomes of mobile learning given that the design and implementation of mobile learning systems fit the principles of SRL” (p. 368).

Summary

This body of research suggests that because of the unique demands of the online environment and the anytime, anywhere nature of mobile learning, SRL is a natural theory from which to understand students’ engagement behaviors and perceptions. Research marrying the concepts of SRL in the context of online learning and mobile learning can provide insight for improving student success.

Chapter 3

Online education has enjoyed a period of growth and development that has made it a familiar fixture in higher education and established it as a viable option for students to access higher education. With this growth, researchers and administrators have turned their attention to retention rates and increasing student success online. At the same time, researchers have begun to track how students are using mobile devices to engage in educational activities (Aslanian & Clinefelter, 2017, 2018; Galanek et al., 2018; Magda & Aslanian, 2019). Yet the research on connections between mobile learning, engagement, and student success is still limited.

The conceptual framework in this study is constituted from theories of mobile learning, Self-Regulated Learning (SRL), and student engagement. Mobile learning definitions provided the context for a learning environment without traditional boundaries. With mobile learning, students can engage in anytime, anywhere learning as the context, environment, and mindset are fluid and adaptable. The online learning environment demands a different level of engagement and discipline for students to be successful, and SRL provides an understanding of how students can regulate their environments and behaviors to be more successful. Key assumptions of SRL are the active, constructive assumption; the potential for control assumption; the goal, criterion, or standard assumption; and the mediation between personal, contextual characteristics and achievement or performance (Pintrich, 2004). Hu and Kuh’s (2001) definition of student engagement is the most applicable to this research since it focuses on student behavior and thinking rather than institutional factors. Hu and Kuh (2001) define student engagement as “the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes" (p.3). Students choosing to engage in mobile learning and practicing SRL may be more engaged learners as a by-product of their self-regulation efforts.

Research Questions/ Hypothesis

RQ1: What impact does mobile learning have on student engagement in an online class?

H_1: Mobile learning has a positive impact on student engagement in an online class.

RQ2: What is the extent of the impact of mobile learning on Self-Regulated Learning constructs?

H_2: Mobile learning has a significant impact on the Self-Regulated Learning constructs of environmental structuring, task strategies, and time management.

RQ3: How does mobile learning affect student success online?

H_3: Mobile learning has a positive impact on student success online.

Research Design

Sampling and Participants

The study population (n = 1,641) is fully online, undergraduate students within one private institution who are enrolled in 8 week-long bi-terms and range in age from 18-66. Two bi-terms occur within one 16-week semester, and students may take between one to three courses in one bi-term. A survey instrument was used to collect data from the participants and used an online delivery method. All actively enrolled students in the online undergraduate school were emailed the informed consent document, notified of the voluntary nature of the study, and provided with the survey link. Participants then opted-in to the study by completing the survey instrument. The survey instrument was distributed at the beginning of the bi-term (March 2020) so that participants could report on their most recent activities from the previous bi-term in their online courses.

From the population, 162 students opted-in to participate in the survey, making a response rate of approximately 10%. This response rate is lower than expected and less than optimal for validity and to decrease bias (Bethlehem, 2010; Fan & Yan, 2010; Leslie, 1972). However, all the participants are undergraduate online students at the same school and completing the survey asking about that shared quality of the group, this uniformity of the group reduces the non-response bias somewhat (Bethlehem, 2010; Leslie, 1972).

Of the 162 respondents, 40 (24.7%) of the respondents reported their age as 18-25 years; 59 (36.4%) reported their age as 26-35 years; 43 (26.5%) reported their age as 36-45 years; 18 (11.1%) reported their age as 46-55 years; and 2 (1.2%) reported their age as over 55 years. These age demographics are representative of the overall online student population (Table 1). Data was also collected on the academic program of the respondents; 7 (4.3%) students were studying in the Applied Sciences, 8 (4.9%) in Arts/Humanities/Languages, 21 (13%) in Business, 1 (.6%) in Communications, 49 (30.2%) in Education, 8 (4.9%) in Health & Wellness, 1 (.6%) in Natural Sciences, 16 (9.9%) in Nursing, 41 (25.3%) in Social and Behavioral Sciences, and 10 (6.2%) in Technology (Table 2). Some majors are over represented in the sample.

Table 1

Participants compared to population by age

		Participants Percent	Population Percent
Age Range	18-25	24.7	24.2
	26-35	36.4	37.5
	36-45	26.5	22.8
	46-55	11.1	12.2
	55+	1.2	3.3
	Total	100.0	100.0

Table 2

Participants compared to population by major

	Participants Percent	Population Percent
Applied Sciences	4.3	.06
Arts/Humanities/Language	4.9	2.3
Business	13.0	19.8
Communications	.06	0
Education	30.2	27.1
Health & Wellness	4.9	6.40
Natural Sciences	.06	.06
Nursing	9.9	7.7
Social and Behavioral Sciences	25.3	27.4
Technology	6.2	7.9
General Studies	0	1.30
Total	100.0	100.0

Survey Instrument

The survey instrument (see Appendix A) used was the Online Self-Regulated Learning Questionnaire (OSLQ), which measures types of behaviors engaged in by the participants (Alanazi & Brown, 2016; Barnard-Brak, Paton & Lan, 2010; Barnard-Brak, Lan, & Paton, 2010). Questions of access to the course through a mobile device and frequency of that access measured levels of engagement in mobile learning. Five additional items were added to gather demographic data.

The short-form OSLQ is a 24 item scale with a 5-point Likert-type response with responses ranging from strongly agree (5) to strongly disagree (1) and was developed from the Motivated Strategies for Learning Questionnaire (MSLQ). However, the MSLQ was developed for the traditional classroom environment and did not consider the change in behavior and practice that the online environment requires. Consequently, the 24 item short-form of the OSLQ was developed from an 86-item question pool comprising the long-form of the instrument (Barnard-Brak, Lan & Patton, 2010; Barnard-Brak, Paton & Lan, 2010). Several studies have shown the OSLQ to produce reliable data with Cronbach alpha internal consistency ranging from .67 to .90 (Alanazi & Brown, 2016; Barnard et al., 2008; Barnard et al., 2009; Barnard-Brak, Paton & Lan, 2010; Barnard-Brak, Lan, & Paton, 2010). The six constructs of self-regulation in the online environment are (1) environment structuring, (2) goal setting, (3) time management, (4) help seeking, (5) task strategies, and (6) self-evaluation (Barnard et al., 2008; Barnard-Brak, Lan, & Paton, 2010). Though apprehensions have been expressed about self-reported measures of SRL concerning the reliability of possible over-estimation (Schraw, 2010), the OSLQ has proven to have satisfactory psychometric properties across two samples of students despite this possible bias (Barnard et al., 2009). Barnard et al. (2009) reported that the chi-squared goodness of fit was significant ($X^2(246)=758.79$, $p<.05$), and adequate internal consistency of the scores was achieved with $\alpha = .90$. Barnard et al. (2009) further explained their results show a X^2/df ratio value of 3.08, the root mean square error of approximation was 0.04, the Non-Normed Fit Index was .95, and the value of the Comparative Fit Index was .96.

Thus, the OSLQ was chosen because of its focus on the online learning environment and SRL behaviors that are most applicable to that learning context. The survey instrument used 11 items from the OSLQ that measure three of the constructs of SRL: environment structuring, time management, and task management. These three constructs were chosen because they proved to be the most relevant or the most likely to have a statistically significant impact based on the previous research (Alanazi & Brown, 2016; Barnard-Brak, Lan, & Paton, 2010; Cho & Shen, 2013; Puzziffero, 2008). Refer to Appendix A for the full survey. While shortening the survey may affect the reliability, this was undertaken with more confidence based on two factors from previous research utilizing the OSLQ. The core research developing and testing the OSLQ pair environment structuring, task management, and time management with a mixture of other constructs from SRL, such as metacognitive strategies, help seeking, goal setting, and critical thinking, while maintaining scores for internal consistency and reliability (Alanazi & Brown, 2016; Barnard-Brak, Lan, & Paton, 2010; Broadbent, & Poon, 2015; Broadbent, 2017; Cho & Shen, 2013; Puzziferro, 2008). Environment structuring, task management, and time management kept internal consistency scores of .92, .92, .89 respectively when they were included in longer and shorter scales (Broadbent, & Poon, 2015; Cho & Shen, 2013; Puzziferro, 2008).

The SRL construct of Environment structuring encompasses behaviors that students engage in to structure their environment for more efficient study based on time, setting, and opportunity. Task management behaviors include methods to choose and prioritize activities that help students complete the tasks necessary for success. The construct of time management includes behaviors that help students plan and allocate their time to best benefit their online class success.

Data Collection and Analysis

The survey administered to the participants collected demographic data for age, gender, and the number of online courses previously completed (see Appendix A). In addition, the survey measured mobile learning with self-reported responses to the frequency of course access by a mobile device (smartphone or tablet) and the activities engaged in through a mobile device. To measure the outcome of student success, participant final course grade and persistence status, enrollment status in the consecutive term, were obtained. The participant final course grade indicated course completion, as grades of A, B, C, D, or F indicate completion to the end of the term; grades of aF (absence failure) and W indicate leaving the course; grades of I indicate course criteria had not yet been met but can still be.

The survey instrument was designed as a branching survey, using two early questions on the survey instrument to divide participants into three groups based on levels of mobile learning– low to moderate, moderate to high, and high (see Appendix A). Low to moderate level mobile learning equals engaging in the online class via a mobile device 1-3 times a week. Moderate to high level of mobile learning equals engaging in the online class via a mobile device 4-8 times a week. A high level of mobile learning equals engaging in the online class via a mobile device 9 or more times a week. These levels were chosen based on the online education culture of the institution, such as requirements for attendance in an online class, the most common number of due dates in a class per week (2-3), and institutional recommendations for how often students should engage in an online class per week. These three levels of mobile learning also offered cut points to create balanced groups for comparison.

The survey was distributed in March 2020 at the beginning of bi-term 2 in the Spring 2020 semester. Participants were asked to think of one class they took in the previous bi-term term to keep in mind as they answered the rest of the questions on the survey. Participants were then added to one of the three groups based on their response to two questions: did they access their course with a mobile device, with the choices being "yes" or "no," and how often they accessed their online class (with or without a mobile device), with the choices being "1-3 times weekly", "4-8 times weekly", and "9 or more times weekly". Only 22 students indicated they did not engage in the one course they named with a mobile device. Due to this low number and that this group was equally distributed between the three levels of frequency of access to the online course, these students were categorized with their respective groups – low to moderate,

moderate to high, and high. The three levels of mobile learning use are independent variables for each research question.

Though the survey Instrument was a branching survey, breaking respondents into two branches of those who answered “yes” to using a mobile device and those who answered “no”, each branch received identical questions. Description of the survey items from here on will refer to the question numbers for each branch of the survey (see Appendix A). Questions 5-15 comprised the items from the OSLQ using Likert scale responses of (5) strongly agree to (1) strongly disagree. The scores from questions 5-15 were summed to create the overall SRL measure (a scale of 11-55), which was used to represent the dependent variable for engagement in research question one. Of these items from the OSLQ, Questions 5-8 were items used to measure the environment structuring construct; Questions 9-12 were items used to measure the task management construct; and questions 13-15 were items used to measure the time management construct (Alanzi & Brown, 2017; Barnard et al., 2008; Barnard et al., 2009; Barnard-Brak, Lan, & Paton, 2010). These question groupings make it possible to sum the individual scale scores for the three SRL constructs. The four environment structuring and four task management items create a summed score scale between 4-20, and the three time management items create a scale score between 3-15. The participants' scores on these three SRL constructs are dependent variables in research question 2.

Question 18 on the survey collected participant’s student ID numbers, which was used to retrieve the final course grade for the course students named at the beginning of the survey. This course grade, either A, B, C, D, F, I, aF, or W (aF = failure due to absences, I= Incomplete, W= withdraw), was a categorical dependent variable used for part of the measure of student success. The ID number was also used to determine the student’s enrollment status in the subsequent term. Students were classified as “Y” – actively enrolled in at least one class in that term, “Y/G” – graduated and actively enrolled in at least one graduate class in that term, “N” – not actively enrolled in at least one class in that term or the next available term, “N/G” – not actively enrolled due to graduation, and “B” – not actively enrolled in the current term, but enrolled in at least one course in the following term which means these students may return to classes after their absence or they may not. This enrollment data created the persistence measurement that was a dependent categorical variable used as part of the measure for student success in research question 3.

Table 3

Study Variables

Variable name	Type	Quantifier
Level of Mobile learning	Independent/Categorical	Low, Moderate, High
SRL Score	Dependent/Ratio	11-55
Environmental Structuring	Dependent/Ratio	4-20
Task Strategies	Dependent/Ratio	4-20
Time Management	Dependent/Ratio	3-15
Course grade	Dependent/Categorical	A, B, C, D, F, aF, I, W
Persistence	Dependent/Categorical	Y, Y/G, N, N/G, B

Research question one asked what impacts mobile learning has on student engagement, as measured by the overall SRL measure. One-Way Analysis of Variance (ANOVA) was used to compare the SRL measures of respondents, the dependent variable, by mobile learning use group, the independent variable. ANOVA is appropriate for this analysis because of the mixture of categorical and ratio variables and that the three categories of mobile learning use are independent groups.

Research question two asked what is the extent of the impact of mobile learning on the SRL constructs of environmental structuring, task strategies, and time management. Three separate one-way ANOVA models were used to analyze levels of mobile learning use and the variability in three dependent variables of environmental structuring, task strategies, and time management. ANOVA was appropriate for this analysis as well because of the mixture of categorical and ratio variables and that the three categories of mobile learning use are independent.

Research question three asks how mobile learning affects student success online, as measured by final course grade and persistence to the next term. Since the course grade and persistence variables are categorical, Chi-Square Crosstabs analysis was used to measure the association of levels of mobile learning, course grade, and persistence.

Limitations

One limitation of the study is the self-reported data collected by the survey. Self-reported data may not be accurate, as students may misjudge their levels of engagement with SRL behaviors (Schraw, 2010). A second limitation is that the results of the study may not be generalizable beyond the type of course the participants of the study were enrolled in, as Finnegan, Morris, and Lee (2009) showed that certain courses naturally require higher levels of engagement or more frequent engagement. A third limitation is the Opt-in nature of convenience sampling used. Convenience sampling does not provide a random sample and may introduce non-response bias, meaning that the sample may not be representative to the population and may have missed selecting students with varying levels of engagement or success (Bethlehem, 2010). Additionally, the topic may not have been of interest to students with low or no levels of mobile learning use causing them to choose not to opt-in and under representing that portion of the population (Bethlehem, 2010; Fan & Yan, 2010). A fourth limitation in the data is the use of composite scores for SRL and its three constructs investigated, which reduces the variability in the individual scores.

Summary

The goal of this chapter was to explain the research questions, hypotheses, and methodology for this study. A description of the population, the survey instrument, and data collection outlined the potential sample for the study, the procedures, and the rationale for the survey design. Chapter 4 will present the data analysis procedures followed and the results of the analysis.

Chapter 4

This study was designed to investigate relationships between online students' use of mobile devices and their online course engagement and academic success. Survey data was analyzed with a variety of quantitative methods to address each research question. Demographic data is first presented, and then the results of each research question follow.

Demographics

For this study, 162 students opted-in to participate in the survey out of 1,641 in the population, creating a response rate of approximately 10%. This response rate is low and less than optimal for validity and to decrease bias (Bethlehem, 2010; Fan & Yan, 2010; Leslie, 1972). However, the uniformity of the group, being all undergraduate online students, reduces the non-response bias somewhat (Bethlehem, 2010; Leslie, 1972).

Based on responses to predetermined survey items, respondents were categorized into three groups of mobile learning representing the levels of mobile access to the course with a mobile device: Low (1-3 times a week), moderate (4-8 times a week), and high (9 or more times a week). Table 4 shows the group percentages. These groups will be used for comparisons in the analysis of research questions 1 and 2.

Table 4

Mobile Learning Group Membership by Level of Mobile Use

		Frequency	Percent
Valid	1-3 times weekly	70	43.2
	4-8 times weekly	55	34.0
	9 or more times weekly	37	22.8
	Total	162	100.0

Note. "times weekly" represents the number of times a student engaged in the online course via a mobile device.

Results

An initial exploratory analysis was undertaken to explore the range of values, outliers, missing values, and distributional characteristics.

Research Question 1

RQ1: What impact does mobile learning have on student engagement in an online class?

H_0: Mobile learning does not impact student engagement or student success.

H_1: Mobile learning has a positive impact on student engagement in an online class.

Descriptive statistics for the dependent variable, mobile learning use levels, and the dependent variable, SRL scores, are presented in Table 5. The Mean values represent composite scores derived from summing the individual survey items. One-way ANOVA was used to analyze the variance in overall Self-Regulated Learning (SRL) scores of respondents by mobile learning group membership (Table 6). There was a statistically significant difference between the three groups as determined by the analysis ($F(2, 159) = 6.570$, p =.002, d =.275). The effect size (d = .275) was determined to be a small effect (Beaudry & Miller, 2016; Cohen, 1977; Hill et al., 2008). A Tukey post hoc test (Table 7) revealed that the SRL scores, the measure of engagement, in the low group were significantly lower than the SRL scores in the high group (HSD = -4.581, p = .001, d =.719) with a large effect size (Beaudry & Miller, 2016; Cohen, 1977; Hill et al., 2008). Tukey is an appropriate post hoc test in this instance because the assumption of homogeneity was not violated, and it is robust with a small sample size (Ashby et al., 2011; Field, 2013). There was not a statistically significant difference in the scores between the low and moderate groups, or between the moderate and high group.

Table 5

Descriptive statistics: Mobile learning (independent), SRL Score (dependent)

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Low	70	40.50	6.201	.741	39.02	41.98	24	55
Moderate	55	42.20	6.035	.814	40.57	43.83	30	53
High	37	45.08	6.525	1.073	42.91	47.26	31	55
Total	162	42.12	6.432	.505	41.13	43.12	24	55

Table 6

One-Way ANOVA, SRL Score

	Sum of Squares	df	Mean Square	F	Sig.	*d*
Between Groups	508.474	2	254.237	6.570	.002	.275
Within Groups	6153.057	159	38.698			
Total	6661.531	161				

Table 7

Tukey HSD, between groups comparison, SRL Score

(I) MobileUse	(J) MobileUse	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	*d*
Low	Moderate	-1.700	1.121	.286	-4.35	0.95	.277
	High	-4.581**	1.264	.001	-7.57	-1.59	.719
Moderate	Low	1.700	1.121	.286	-0.95	4.35	.277
	High	-2.881	1.323	.078	-6.01	0.25	.458
High	Low	4.581**	1.264	.001	1.59	7.57	.719
	Moderate	2.881	1.323	.078	-0.25	6.01	.458

*. The mean difference is significant at $\alpha < .05$.

**. The mean difference is significant at $\alpha < .01$.

The analysis showed partial significance for the SRL scores with a large effect between the low mobile learning group and the high mobile learning group. The test of the residuals showed model adequacy. Therefore, the hypothesis that mobile learning does not impact student engagement is rejected. The hypothesis that mobile learning has a positive impact on student engagement is not rejected.

Research Question 2

RQ2: What is the extent of the impact of mobile learning on Self-Regulated Learning constructs?

H_2: Mobile learning has a significant impact on the Self-Regulated Learning constructs of environment structuring, task strategies, and time management.

Descriptive statistics for the three dependent variables, environment structuring, task management, and time management, are presented in tables 9, 10, and 11, respectively. Three separate one-way ANOVA tests were performed to analyze the variance of each of the SRL constructs of environment structuring, task strategies, and time management strategies with each group of mobile learning use. The results of each are presented together in Table 12 for comparison. The results of each construct are addressed individually.

Table 8

One-way ANOVA, SRL Environment Structuring, Task Strategies, Time Management

		Sum of Squares	df	Mean Square	F	Sig.	*d*
Environment Structuring	Between Groups	11.230	2	5.615	.885	.415	.104
	Within Groups	1009.320	159	6.348			
	Total	1020.549	161				
Task Strategies	Between Groups	166.703	2	83.351	8.065	.000	.303
	Within Groups	1643.328	159	10.335			
	Total	1810.031	161				
Time Management	Between Groups	40.511	2	20.255	3.448	.034	.202
	Within Groups	933.934	159	5.874			
	Total	974.444	161				

Environment Structuring. The descriptive statistics for the SRL construct of environment structuring are displayed in Table 9. The mean scores represent composite values created from summing the individual items related to environment structuring behaviors. For the ANOVA with environment structuring (Table 8), there was not a statistically significant difference between the groups ($F(2, 159) = .885$, $p = .415$).

Table 9

Descriptive Statistics: SRL Environment Structuring scores

					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
Low	70	16.96	2.590	.310	16.34	17.57	12	20
Moderate	55	17.31	2.340	.316	16.68	17.94	12	20
High	37	17.62	2.639	.434	16.74	18.50	8	20
Total	162	17.23	2.518	.198	16.84	17.62	8	20

The model failed assumptions of normality, so a check for outliers was run, and one outlier removed. The model adequacy check was tested again but did not have an impact on the model. The results of the ANOVA were not affected by this model check.

Task Strategies. The descriptive statistics for the SRL construct of task strategies are displayed in Table 10. The mean scores here represent composite values created from summing the individual survey items related to task strategy behaviors. For the ANOVA with task strategies (Table 8), there was a statistically significant difference between the groups ($F(2, 159) = 8.065$, $p = .000$, $d = .303$) with a moderate effect size (Beaudry & Miller, 2016; Cohen, 1977; Hill et al., 2008).

Table 10

Descriptive Statistics, SRL Task Strategies scores

					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
Low	70	12.46	3.001	.359	11.74	13.17	4	20
Moderate	55	13.40	3.241	.437	12.52	14.28	4	19
High	37	15.08	3.554	.584	13.90	16.27	7	20
Total	162	13.38	3.353	.263	12.86	13.90	4	20

Tukey's post hoc test was chosen to analyze the differences between the groups for task strategies because the assumption of homogeneity of variance was met, so a more conservative test was not needed (Field, 2013). The Tukey post hoc analysis (Table 12) revealed that the task strategy construct scores for the low group were significantly lower than the scores for the high group (HSD = -2.624, $p = .000$, $d = .796$). The scores for the moderate group were significantly lower than the scores for the high group (HSD = -1.681, $p = .040$, $d = .494$). The effect size between the low group and the high group was large, and the effect size between the moderate group and the high group was moderate (Beaudry & Miller, 2016; Cohen, 1977; Hill et al., 2008).

The model adequacy checks for task strategies showed no violations of assumptions.

Time Management. The descriptive statistics for the SRL construct of time management are displayed in Table 11. The mean scores represent composite values created from summing the individual items related to task strategy behaviors. For the ANOVA with time management, there was a statistically significant difference between the groups ($F(2, 159) = 3.448$, $p = .034$, $d = .202$), with a small effect size (Beaudry & Miller, 2016; Cohen, 1977; Hill et al., 2008).

Table 11

Descriptive Statistics, SRL Time Management scores

					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
Low	70	11.09	2.547	.304	10.48	11.69	3	15
Moderate	55	11.49	2.159	.291	10.91	12.07	7	15
High	37	12.38	2.553	.420	11.53	13.23	4	15
Total	162	11.52	2.460	.193	11.14	11.90	3	15

Tukey’s post hoc test was chosen to analyze the difference between the levels of mobile learning for time management because the assumption of homogeneity of variance was met, so a more conservative test was not needed (Field, 2013). The Tukey post hoc analysis (Table 12) also revealed that the time management construct scores for the low group were significantly lower than the scores for the high group (HSD = -1.293, $p = .026$, $d = .505$) with a slightly larger effect size (Beaudry & Miller, 2016; Cohen, 1977; Hill et al. 2008).

Table 12

Tukey HSD, between groups comparison, SRL Task Strategies and Time Mgmt

Dependent Variable	(I) Mobile Use	(J) Mobile Use	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	*d*
SRL Task Strat Score	Low	Moderate	-0.943	.579	.237	-2.31	.43	.301
		High	-2.624**	.653	.000	-4.17	-1.08	.796
	Moderate	Low	0.943	.579	.237	-.43	2.31	.301
		High	-1.681*	.684	.040	-3.30	-.06	.494
	High	Low	2.624**	.653	.000	1.08	4.17	.796
		Moderate	1.681*	.684	.040	.06	3.30	.494
SRL Time Mgmt Score	Low	Moderate	-0.405	.437	.624	-1.44	.63	.169
		High	-1.293**	.493	.026	-2.46	-.13	.505
	Moderate	Low	0.405	.437	.624	-.63	1.44	.169
		High	-0.887	.515	.200	-2.11	.33	.376
	High	Low	1.293**	.493	.026	.13	2.46	.505
		Moderate	0.887	.515	.200	-.33	2.11	.376

*. The mean difference is significant at $\alpha < .05$.
**. The mean difference is significant at $\alpha < .01$.

The analysis showed significance for two of the three SRL constructs, task strategies and time management. The effect sizes between the low and high groups were largest for the task strategies construct and small for the time management construct. The effect sizes between the moderate and the high group were moderate for the task strategies construct.

The model adequacy checks reveal extreme values accounted for .02% of the total cases. While the design was unbalanced, the researcher decided the sample size was sufficient to mediate the effect of the extreme values had on the group means, and therefore the values were retained.

Thus, the hypothesis that mobile learning has a significant impact on the SRL constructs of environment structuring, task strategies, and time management is partially supported and not rejected.

Research Question 3

RQ3: How does mobile learning affect student success online?

H_3: Mobile learning has a positive impact on student success online.

A Chi-Square test of independence Crosstabs analysis was used to analyze the association between mobile learning and the two measures of student success online – course grade and persistence to the next term. This method was chosen because the categorical dependent variable has three levels, and both course grade and persistence have 7 and 5 levels, respectively.

The overall crosstabs analysis of the levels of mobile use and course grade did not show a significant association ($X^2 = 8.553$, *df* (10), $p = 0.575$) (Table 14, 15). Additionally, the descriptive count table of the course grade variable (Table 13) shows the lack of variation in the distribution of the grades. The Chi-Squared test showed that nine value cells (50.0%) had an expected count of less than 5 when the minimum expected count was .46, which is a result of the lack of variation in the grades reported.

Table 13

Crosstab Count, Course Grade

		N*	A	B	C	F	W	Total
MobileUse	low	14	36	13	3	2	2	70
	Moderate	7	40	6	1	1	0	55
	High	5	22	7	2	1	0	37
Total		26	98	26	6	4	2	162

Note. *N = not reported. Grade data was not available for these cases.

Table 14

Chi-Square Tests, Course Grade

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	8.553	10	.575
Likelihood Ratio	9.420	10	.493
N of Valid Cases	162		

Table 15

Symmetric Measures, Course Grade

		Value	Approximate Significance
Nominal by	Phi	.230	.575
Nominal	Cramer's V	.162	.575
N of Valid Cases		162	

In consideration of the violations, the data was manipulated to eliminate grades C, F, and W and non-response variables. The researcher reexamined the association between mobile use and course grade and found no statistical significance (X^2 = 2.834, *df* (2), *p* = .242).

The analysis of the levels of mobile learning with persistence to the next term also did not show a significant association (X^2=12.786, *df* (10), *p* = 0.236) (Table 17, 18). In the Chi-Squared test, eight value cells (44.4%) had an expected count of less than 5 when the minimum expected count was .91. This lack of variance affected having an adequate test. Additionally, the descriptive count table for the persistence variable (Table 16) shows the lack of variation in the distribution of enrollment status for each level of mobile learning. However, the students who did persistent to active enrollment in the following term had the highest percentages at each level than students who did not – low group, 52.9%; moderate group, 54.5%; high group, 70.3%. In Table 15, “B” represents students not enrolled in the current bi-term but were enrolled in the next bi-term, “N” represents students who were not actively enrolled, “N/G” represents students who were not actively enrolled due to graduate, “Y” represents students who were actively enrolled in the current bi-term, and “Y/G” represents students who were actively enrolled but had graduated and enrolled in graduate school.

Table 16

Crosstab Count, Persistence

		Nr*	B	N	N/G	Y	Y/G	
MobileUse	Low	14	7	10	1	37	1	70
	Moderate	7	6	4	5	30	3	55
	High	5	2	3	1	26	0	37
Total		26	15	17	7	93	4	162

Note. Nr= not reported. Enrollment and persistence data was not available for these cases

Table 17

Chi-Square Tests, Persistence

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	12.786	10	.236
Likelihood Ratio	13.057	10	.221
N of Valid Cases	162		

Table 18

Symmetric Measures, Persistence

		Value	Approximate Significance
Nominal by Nominal	Phi	.281	.236
	Cramer's V	.199	.236
N of Valid Cases		162	

In consideration of the violations, the persistence data was manipulated to eliminate categories Nr, Y/G, N/G, and B. The researcher reexamined the association between mobile use and persistence and found no statistical significance (X^2 = 2.153, *df* (2), *p* = .341).

Summary

This chapter provided the findings of the quantitative analysis for each of the research questions investigating the impacts of mobile learning, Self-Regulated Learning, and student success. Students using the highest level of mobile learning also had higher SRL scores. The SRL constructs of task strategies and time management were both significantly connected to the greater levels of mobile learning use, moderate and high. A significant association between the levels of mobile learning and course grade or persistence to the next term was not apparent. The following chapter will discuss the implications, limitations, and recommendations of these findings.

Chapter 5

Online education has increased in use, prominence, and scholarship over the last two decades, with many advantages for students and higher education institutions. As personal and mobile technologies rapidly evolved to become part of the fabric of many students' lives, successes and challenges have become apparent. While online education and mobile learning widen the access to higher education for many more students, the success rates of students online vary greatly among institutions, programs, and delivery type (Bawa, 2016). Maintaining student enrollment in online programs and helping students stay engaged in their online studies have remained a concern for many institutions.

Since mobile usage for online courses has been tracked, the number of students reporting using mobile devices to access their course has increased, as well as the number of students desiring to use a mobile device for their online courses (Aslanian & Clinefelter, 2016, 2017; Clinefelter et al., 2019; Magda & Aslanian, 2018). The research on the impact of mobile learning on student success online is still exiguous. However, research on mobile learning and student success has the potential for identifying the behaviors of these students that are more likely to lead to academic success. This research was undertaken to investigate the impacts of mobile learning use on students' engagement and their academic success in the online environment. What follows is a summary of the findings from this research, the conclusions, calls for further research, and recommendations.

Summary

Students in the sample were grouped into three categories of mobile learning use based on their self-reported responses, with 43.2% using mobile learning 1-3 times a week, 34.0% 4-8 times a week, and 22.8% 9 or more times a week. In the initial responses, it was noteworthy that very few students indicated they did not use a mobile device to engage in their online course in the targeted time interval (one 8-week bi-term). One of those students noted that he or she would use a mobile device to check grades. Another noted that he or she would have used a mobile device to engage in the class except that the content was “too extensive to use my phone for anything other than maybe reading my assigned reading materials for them.” The activities within the online course that students engaged in through mobile learning that were tracked were discussion boards, asking questions, taking a test, submitting work, reading content, and watching videos. Of the activities, reading content had the highest percentage of use at 90% using mobile learning for this course activity; discussion boards had the second highest percentage at 75.3%; watching videos had the third-highest percentage of use at 60.5%. Mobile learning was used to submit work 40.7% of the time, to take a test 31.5% of the time, and to ask questions only 26.5% of the time. How often students used a mobile device to access their grades was not tracked.

Research Question 1

To the question, if mobile learning has an impact on student engagement (as measured by the SRL score) in an online course, the analysis found that the variance in the SRL scores was significant for students with the highest level of use, 9 or more times a week. This analysis supported the hypothesis that mobile learning has a positive impact on student engagement in the online class. This finding is also in agreement with Morris and Fennigan (2009), who found that students who completed online courses engaged in online learning behaviors more frequently. The subsequent natural question is what online learning behaviors might be more impactful than others.

The design of the Online Self-Regulated Learning Questionnaire (OSLQ) organizes the survey items by the constructs of SRL. The construct of environment structuring describes behaviors that students may engage in to choose or structure their study environments in a way to benefit their study time and academic abilities. The construct of task management describes behaviors that students may engage in to select and prioritize what is necessary to complete tasks in their online courses. The third construct that was measured in this study was time management, which describes behaviors that students may engage in to manage and make the best use of their time while studying or completing tasks for their online courses.

Research Question 2

The hypothesis that mobile learning has a significant impact on the Self-Regulated Learning constructs of environment structuring, task strategies, and time management was partially supported. Environment structuring was not significant based on the different levels of mobile learning. However, the observed average scores for all the levels of mobile learning engagement were higher than the observed average scores for the other two constructs of SRL, task management and time management. This suggests that the learners' environment may not change often or that it may be critical to SRL overall but does not change by the frequency of engagement of the learner.

The analysis showed that scores for task strategies did vary significantly between the groups of mobile learning levels. The differences between mobile learning use for the low and high groups were statistically significant as well as for the moderate and high groups. However, there was not a significance in variation between the low and moderate groups. Additionally, the variance in the scores for the construct of time management was significant between the low and high groups. These findings are similar to those of Puzziferro's study (2008) that time management and task strategies were significant to academic performance, and that task strategies were a significant predictor of the course grade. These two categories, time management and task strategies, were also found to be predictors of better course grades by Cho and Shen (2013).

Research Question 3

The data from the analysis of the association between mobile learning and student success (course grade and persistence to the next term) lacked variation in grade distribution and enrollment status. The overall crosstabs analysis was not significant for persistence or course grade. It was observed that students with the moderate level of mobile learning earned more A grades than the other two levels of mobile learning. The null hypothesis that mobile learning has an impact on student success is not rejected based on this data.

By and large, students in the sample earned As and Bs in the classes they noted having used mobile learning. The lack of variance in the grade distribution may indicate the desire of the students to show their best work and choose for the survey the class in which they think they performed the best. The greater prevalence of A and B grades could also be a result of who choose to take the survey. Since the survey sample was created from students opting-in to participate, perhaps that appeals to students who are higher achievers.

Conclusions

The assumptions of mobile learning are brought together in this definition: mobile learning is situationally based on the mobility of learners and learning contexts, allowing for fluidity of personal learning in time, content, and context, and mediated through technology (El-Hussein & Cronje, 2010; Sharples et al., 2016). In this study, the results of one research question help inform the results of each of the other research questions. For example, understanding that mobile learning can have a positive impact on the SRL behaviors associated with time management and task strategies, as measured in research question 2, helps inform the finding from research question 1. This is an indication of the interconnectedness of the behaviors of mobile learning and self-regulated learning. As such, the following section will be organized by the main conclusions drawn from the results and the available literature that helped inform this study.

Self-Regulated Learning Constructs

Environment Structuring. Even though the SRL construct of environment structuring was not significantly different among the three groups of mobile learning users, the average scores for environment structuring were higher for each of the three levels of mobile learning users than either of the other two SRL constructs. This supports the mobility and fluidity characteristic of mobile learning itself, as noted in the definition by El-Hussein and Cronje (2010) and Sharples et al. (2016). Students in this present study leveraged the ability to engage in coursework at any place of their choosing so that learning could happen despite their location and environment. Puzziferro’s 2008 study of online learners and self-regulation established that environment management and structuring were significant for students’ success in the online course. Puzziferro’s study used the parent-survey of the OSLQ, the Motivated Strategies for Learning Questionnaire, to highlight behaviors that are more meaningful in the online environment, which helped develop the online specific OSLQ.

Interestingly, Puzziferro’s conclusions on the research noted that students showed high confidence in using the online technologies (such as attaching documents, checking email, and participating in online discussion forums) and suggested student support efforts should shift to less technology training and more academic support. Similarly, this present research perhaps notes a shift in student behavior and confidence with online learning and mobile technologies. All students in this study used environment structuring behaviors more often than other behaviors, as evidenced by the highest average scores for environment structuring, perhaps because it is simply part of their approach to online learning. Environment structuring behaviors may include choosing a study location and time to reduce distractions, choosing a comfortable place to study, or an environment that fosters efficiency for study. The current research echoes the findings of Barnard-Brak, Patton, and Lan (2010), who did not include mobile access as a point of study, that for online students the SRL construct of environment structuring was not statistically significant but had higher median scores for all the students in the study than all but one of the other SRL constructs.

Time Management. The time students dedicated to their online learning through a mobile device and how that time was managed was more significant for students with the highest levels of mobile learning engagement. Examples of time management in this context might be scheduling regular study times and when to engage in the online class or allocating extra study time for online classes. The time management finding is similar to the importance of time management and time on task in the research of Puzziferro (2008), Cho and Shen (2013), and Morris and Fennigan (2009). The detailed research of Korkofingas and Marci (2013) also found that the time spent in an online class does matter to students' success, but the impact varies by the assessment type. Students who spent more time on informal assignments may perform better, but that same effort may not make any noticeable difference in formal assignments (2013). Korkofingas & Marci (2013) also noted that greater amounts of time spent in the online course spread over more sessions produced better performance on informal assignments. In practical terms, if students are using their mobile devices to read course content and participate in discussion forums, both of which are informal assignments, that may translate to better performance on formal assignments such as tests, projects, and papers.

Task Management. Time management further relates to the third SRL construct of task management, which was the other construct to have statistical significance in this study. In the same manner as time management, students with the highest levels of mobile learning engagement practiced task management strategies to a greater degree. For example, they may read content aloud to increase focus, prepare questions before joining a chat or discussion board, or work extra problems to master the content. The higher significance of task strategies for the high level of mobile learning over the moderate and low levels suggests that engaging in the course via mobile learning is itself a task strategy and may lend those students to plan more strategies for success in their courses. Although in this present study, the SRL construct scores were not tested with the course grades, the increased use of task strategies for the highest group of mobile users complements the research of Broadbent and Poon (2015) who found that effort regulation had positive correlations with academic achievement. Furthermore, effort management was used more by fully online students compared to hybrid course students in Broadbent's (2017) results, and only time and effort management positively predicted course grades.

Mobile Learning, Course Grades, and Self-Regulated Learning

The final course grade data suggests that the course grade may only be connected to the moderate level of mobile learning use, though this is assumed just from observation. It is worth noting that overall, the majority of the final course grades for students in this study were higher-achieving As and Bs. These two findings taken together seem to suggest that a moderate level of mobile learning engagement might be just as effective as a higher level of mobile learning engagement.

Of the students in the sample, very few earned an F, only one student received a W (withdraw), and no students earned a D. Again, this is a conspicuous absence because of the lack of variance in the course grades and for what it might suggest about SRL. Self-Regulated Learning behaviors and activities are “mediators between personal and contextual characteristics” (Pintrich, 2004). Despite the different environments, backgrounds, contexts, and characteristics, the students in this sample were able to reach similar academic achievement.

Just as Barnard et al. (2008) concluded, although grade performance does not seem strongly related to SRL scores, the research does not show an absence of an impact on students’ behaviors. Choosing to use mobile learning may be a self-regulatory behavior and be the first of many impactful behaviors students choose to engage with to benefit their learning and academic success.

Frequency of Mobile Learning Use

The research results highlighted several findings related to the frequency of students' activities in the course and mobile learning use. The respondents in each group of mobile learning use – 1 to 3 times a week, 4-8 times a week, and 9 or more times a week – were evenly distributed between the three levels, which also supports the fluidity of learning assumption of mobile learning as well. Fluidity of learning accepts that students utilizing mobile learning carry their learning activities through different contexts and circumstances. So that students not only assume they can engage in learning anywhere but also at any time and any way they choose.

Students in this sample consider mobile learning as a viable option to engage in their course as frequently as they wish to.

The three levels of mobile learning use were not indicators of how much a student did or did not access the course in total, just how often a student accessed and engaged in the course with a mobile device. These engagements with the course could be in addition to traditional access through a laptop or desktop computer. This observation might explain why students in the low group earned more A grades than other course grades. This may also explain the significantly higher SRL task strategies scores for those in the high group. Students who are using a mobile device to engage in their course work 9 or more times a week may be doing so as a task strategy itself, perhaps offering better opportunities for those students to complete tasks.

Limitations

The results of the present research may not be generalizable beyond the Blackboard system since different LMS enables different features or mobile compatibility. Additionally, due to the timing of the data collection (start of a new academic term), the results do not adequately capture the SRL behavior and mobile learning use of students who may not have succeeded in the previous term. The smaller sample size and being a convenience sample also highlight the limitation of inadequate coverage of students who engage in mobile learning or Self-Regulated Learning less. Because of this, data is not available for what behaviors or lack of behavior may negatively impact success.

Future Research

The present research provides insights on student behaviors that might lead to success, and it highlights more opportunities for inquiry to increase our understanding of the growing theory of mobile learning. Further research should focus on when and why students choose to use mobile learning so that faculty, support staff, and administrators can better understand the behaviors that lead to success and which ones do not. The parameters of the present study did not allow time to follow up with students who identified as having used mobile learning. Nevertheless, a subsequent question from the results is what motivates these students to choose mobile learning, and if mobile learning is a primary mode of access to their online courses or a supplemental method of access.

Additionally, more research is needed on mobile learning's impact on grades or other measures of student success. Course grades are just one measure of academic success for students. Research is needed to investigate if mobile learning has a more immediate impact on assignment grades within a course. Persisting with the class is another measure of success – staying enrolled in a class and actively enrolling in the next term. However, persistence could not be confidently associated with students' success in this study. While the majority of the students in the study maintained active enrollment in the class and the next term, an association was not found with their course grade or level of mobile learning. Future research may indicate new ways to measure the possible impact of mobile learning on students' course persistence. More research on mobile learning with students who do not succeed in the course will fill the gaps in understanding the nuances of mobile learning behavior and how it complements or impedes student success.

Future research should aim to replicate this study with a broader study population to capture a better representation of online students' use of mobile learning and how it impacts their engagement and success. The timing of the data collection for this research, March 2020, may have had two negative effects on the study sample. Making the survey available and asking students to participate at the beginning of a new term may have unintentionally excluded students who did not perform academically well and may have dropped out of the program. Additionally, approximately two to three weeks into the data collection, businesses, daycares, and schools began to close due to the COVID-19 pandemic safety protocols mandated by states. While these closures did not change the structure of school for this population, being all online students, it undoubtedly affected other parts of their lives, which made responding to a voluntary survey unimportant.

Interestingly, educators have begun to consider the factors that breed success for online education due to the sudden switch to online delivery for the majority of schools due to COVID-19. The increased focus creates a unique opportunity to understand student and faculty attitudes about online instruction and mobile learning. What may have been a convenience before the COVID-19 pandemic, now might be a necessity. More research is needed on how to build quality instruction that can be delivered via more than one platform – desktop browsers, mobile browsers, mobile apps, and campus Learning Management Systems.

Lastly, more research on how to cultivate Self-Regulated Learning behaviors for online students is needed to inform student support practices, online course design, and online pedagogy. The research on Self-Regulated Learning in the online environment is still relatively young (Barak et al., 2016; Barnard et al., 2008; Barnard et al., 2009; Barnard-Brak et al., 2010; Fisher & Baird, 2009; Puzziferro, 2008; Sha et al. 2011; Usta, 2011). Continued research is needed to add to this field in general and to keep pace with the change in online technologies that may impact education.

Recommendations

The number of students desiring to use mobile learning, as indicated by Clinefelter et al. (2019), and the regular use of mobile learning hinted in the present study suggests the demand for mobile learning by the students preparing to enter college. Younger students may be more expectant to use their phones for all parts of their lives, including educational pursuits. Additionally, non-traditional students with work and family obligations may plan to use their phones and tablets for education as well because it offers flexibility, convenience, or adaptability for their lives. It is clear that mobile technology is part of the structure of everyday life now for most (Pew Research, 2019), and that mobile technology is an indispensable tool students will use to reach their educational goals. This truth has many implications for the development of course design and student success supports and further research on the impact of this technology.

The first recommendation is to make online learning course design more mobile friendly. Nearly 77% (144 students) of students in this study sample indicated they used a mobile device to engage in their class. Additionally, those students are engaging in mobile learning with regular frequency. Fisher and Baird (2014) asserted that the structure of the course largely determines the extent to which students will engage in an online learning community, and this truth seems to have more critical implications for students desiring to use mobile devices and mobile learning. Two students from this study indicated they would have used a mobile device if the course content or format was more compatible with the mobile format. Average course design for a standard browser will not translate well to a mobile-enabled browser or even the LMS app (if one is available), making content less easy to read, inaccessible, or page navigation buttons may disappear. The method used to set up assignments, content, and assessments can all be affected by the method of access to the course - through a desktop browser versus a mobile browser or app.

Online courses should be designed with more interactive content when possible, rather than a long-text format that is often a fallback for content delivery online. An interactive design approach benefits all online students, and interactive content can incorporate activities that enable the use of features and activities native to smartphones and tablets such as quick access to images and pictures, video calls, texting, and other types of communication apps.

Online mobile friendly courses should be designed to foster self-regulatory behaviors in students. Barnard-Brak, Patton, and Lan (2010) note the importance of developing self-regulatory behaviors in first-time online students since adjusting to that structure of learning is a factor for students beginning online study. Even though online learning has grown in prominence and use in the last ten years, the need still exists since new students are beginning online education each academic term.

Online course development for interactivity and fostering self-regulation does not need to belong to Instructional Designers only but should be a shared responsibility with online faculty. A second recommendation is to improve online pedagogy and faculty development around online teaching and mobile technologies. Practically speaking, in light of the present findings on the significance of time management strategies and task management strategies, faculty should communicate the time on task expectations for particular assignments, especially multi-level projects that may extend through weeks of the online course. For example, if students know that they are expected to spend two to three hours gathering research for a report, then they can focus their time management efforts better. Communicating expectations about course performance or task management increase the likelihood that students will meet or exceed those expectations (Baxter, 2012; Korkofingas & Marci, 2013). Providing detailed assignment instructions that include expectations and suggestions for success on the assignment (when variation on the finished product is expected) helps build self-regulatory behaviors and increase student satisfaction and success in the course (Jackson et al., 2010). Communicating expectations would benefit the students in this study who were already employing task management strategies. It is essential to train online faculty on how to best use the features of the LMS to encourage self-regulated behaviors and how to make their content more adaptable for mobile learning.

A third recommendation is to design online orientations that incorporate mobile technology use as content in the orientation. The higher percentage of students in the study engaging in mobile learning indicates the desire and propensity of students to use the tool for their education. That students in the lower levels of mobile learning also had lower levels of task management and time management behaviors may suggest they do not know the best or most efficient ways to use their devices for their academic success. Online orientation for online students is the first best opportunity to direct students' minds to best practices for their success. The use of mobile devices to stay informed, connected, and engage in their learning platform should be communicated and demonstrated in the orientation. The orientation should have students actively engage in the LMS and the LMS app if they wish to. This suggestion is supported by the research on successful design and use of orientation for online students by Herx, 2012; Jones, 2013; and Wozniak et al., 2012.

The fourth recommendation from this research is to encourage students to consider their smartphones or tablets as a viable tool for their educational success. Encouraging students to use their mobile devices is similar to the suggestions about clearly communicating expectations about time and assignment strategies. The suggestion that student could or should use their mobile devices as an education tool might create more opportunities for access that may not have been considered before. Tips for success often communicated to online students emphasize needing a computer, which is most often interpreted as a desktop or laptop computer. Adding 'smartphone or tablet' to the list with 'computer' suggests the possibility for the student. That a student could use a mobile device for their coursework is not yet a common assumption of students. The 2018 ECAR study of students and technology found that three-quarters of faculty discouraged students from using smartphones (Galanek et al., 2018). Mixed attitudes and personal preference surrounding mobile devices leads to unclear expectations for mobile device use. Particularly, if students have been in a class or educational environment where phone use was discouraged or not allowed, this may cause students to not consider their phone or tablet as a tool for their success. The mere suggestion that students can use their phone or tablet as an education tool may increase their communications and their flexibility, convenience, or satisfaction with their online learning experience. Smartphones and tablets should be treated as a resource students have, among others, to meet their educational goals.

The results of this research plus the available literature are encouraging that students are taking advantage of the current technologies to contribute to their success and incorporate college into their lives. Increasing knowledge about what behaviors and supports benefit online students the most contributes to improved pedagogy and more appropriate supports for students. Mobile learning is still a relatively young theory with a limited number of applications available in the literature. The findings and accompanying literature help inform the developing theory of mobile learning. For instance, the behavior of the group of students in the study may signal a shift in mobile technology acceptance and application in the higher education setting. The absence of literature with a large sample of mobile learning users, coupled with the overwhelming majority of students in this sample using mobile learning, is one indication that the trend is changing. As technology continues to evolve, mobile learning theory will be even more applicable across traditional and non-traditional forms of higher education.

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Appendix A

Survey Instrument

Q1: In the past 4 months, have you used a mobile device (smartphone or tablet) to access your online courses?

A: yes or no

Here the student will get a set of questions depending on their answer of yes or no. QY indicates questions for students who answered yes for Q1; QN indicates questions for students who answered no to Q2

Q2Y: For the following questions, think of one particular online course which you accessed with a mobile device (smartphone or tablet). What is that course? ______________

Q3Y: How often did you access your online course through a mobile device?

A: 1-3 times weekly
4-8 times weekly
9 or more times weekly

Q4Y: Which activities have you engaged in through your mobile device?

Choose as many that apply
A: discussion board
ask questions
take test/quiz
submit other work
read content
watch videos

For the next set of questions, rate your response to the statement.

Q5Y: I choose the location where I study to avoid too much distraction.

Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q6Y: I find a comfortable place to study.

Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q7Y: I know where I can study most efficiently for online courses.

Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q8Y: I choose a time with few distractions for studying for my online courses.

Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q9Y: I try to take more thorough notes for my online courses because notes are even more important for learning online than in a regular classroom.

Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q10Y: I read aloud instructional materials posted online to fight against distractions.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q11Y: I prepare my questions before joining in the chat room and discussion.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q12Y: I work extra problems in my online courses in addition to the assigned ones to master the course content.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q13Y: I allocate extra studying time for my online courses because I know it is time-demanding.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q14Y: I try to schedule the same time every day or every week to study for my online courses, and I observe the schedule.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q15Y: Although we don't have to attend daily classes, I still try to distribute my studying time evenly across days.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q16Y: What is your age range
18-25, 26-35, 36-45, 46-55, 55+

Q17Y: Please Choose your Major field
(drop-down menu of choices)

Q18Y: Please provide your student ID number

Q2N: For the following questions, think of one particular online course. What is that course?

____

Q3N: How often did you access your online course?
A: 1-3 times weekly
4-8 times weekly
9 or more times weekly

Q4N: in a typical week which activities did you engage in?
Choose as many that apply
A: discussion board
ask questions
take test/quiz
submit other work
read content
watch videos

For the next set of questions, rate your response to the statement

Q5N: I choose the location where I study to avoid too much distraction.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q6N: I find a comfortable place to study.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q7N: I know where I can study most efficiently for online courses.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q8N: I choose a time with few distractions for studying for my online courses.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q9N: I try to take more thorough notes for my online courses because notes are even more important for learning online than in a regular classroom.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q10N: I read aloud instructional materials posted online to fight against distractions.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q11N: I prepare my questions before joining in the chat room and discussion.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q12N: I work extra problems in my online courses in addition to the assigned ones to master the course content.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q13N: I allocate extra studying time for my online courses because I know it is time-demanding.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q14N: I try to schedule the same time every day or every week to study for my online courses, and I observe the schedule.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q15N: Although we don't have to attend daily classes, I still try to distribute my studying time evenly across days.
Likert Scale 5 (strongly agree) to 1 (strongly disagree)

Q16N: What is your age range
18-25, 26-35, 36-45, 46-55, 55+

Q17N: Please Choose your Major field
(drop-down menu of choices)

Q18N: Please provide your student ID number