Winter March 7th, 2018

THE RELATIONSHIP OF SELF-REGULATED LEARNING AND ACADEMIC RISK FACTORS TO ACADEMIC PERFORMANCE IN COMMUNITY COLLEGE ONLINE MATHEMATICS COURSES

Jim E. Dunnigan Dr.
Seattle Pacific University

THE RELATIONSHIP OF SELF-REGULATED LEARNING AND ACADEMIC RISK FACTORS TO ACADEMIC PERFORMANCE IN COMMUNITY COLLEGE ONLINE MATHEMATICS COURSES

A dissertation submitted by

Jim E. Dunnigan

to

Seattle Pacific University

in partial fulfillment

of the requirement for the degree of

DOCTOR OF EDUCATION

The Relationship of Self-Regulated Learning and Academic Risk Factors to Academic Performance in Community College Online Mathematics Courses

By Jim Dunnigan

A dissertation submitted in partial fulfillment

Of the requirements for the degree of

Doctor of Education

Seattle Pacific University

2018

Approved by ______________________________
(Arthur Ellis, Ed.D., Chairperson of the Dissertation Committee)

____
(William Nagy, Ph.D.)

____
(David Wicks, Ed.D.)

Program Authorized to Offer Degree

School of Education

Date MARCH 2018

____
(Rick Eigenbrood, Ph.D., Dean, School of Education)

Copyright Page

Signature ____________________

Date 4/5/18

Table of Contents

List of Figures

List of Tables

Dedication

This work is dedicated to my wife Francine. I could not have completed this dissertation without her encouragement, patience, and support. Her belief in me never wavered and that made all the difference. I would also like to thank my teenage children Sara, Megan, and Trevor. While they never quite understood why I continue to go to school, they tolerated my never-ending “dissertating”. Kids, I can now proudly say I am no longer “ABD”! I owe my desire to make a difference and pursue academics to all my teachers at St. Ignatius College Preparatory high school in San Francisco.

Acknowledgements

My journey began with inspiration from Dr. Robert Hughes at Seattle University. Dr. Hughes encouraged me to pursue my doctorate as he described it as the “coin of the realm” in higher education. I now understand why he said this. His mentorship made a difference in helping me become the educator I am today.

I would especially like to thank my dissertation committee. I appreciate Dr. Ellis for his support and guidance as my dissertation committee chair. His thoughtful questions, superb editing, and continuous support was instrumental in my completing this dissertation. Thank you Dr. Nagy for your expertise on my statistics in my research. I greatly appreciated our long talks and your support was invaluable. Thank you to Dr. Wicks, your expertise with online learning was invaluable.

I also appreciate the guidance and support of Dr. Stephanie Delaney who helped me make the connections at her institution to conduct my research. She helped me understand the nuisances and challenges of the community college environment and was always willing to talk with me when I ran up against obstacles.

My research could not have been completed if not for the support and follow-through of the community college mathematics teachers who agreed to participate in my study. I thank the teachers for their commitment to my research and for taking their valuable time to participate in my study.

I especially appreciated the support from the executive director at my research institution who made sure my IRB made it through all the requirements. His extra efforts on weekends and evenings really made a difference in making sure I could keep my research on schedule.

Abstract

Completion of required mathematics courses in a community college program of study can be a critical factor in a student's academic success and degree completion. Underprepared, nontraditional students who take mathematics courses online in a community college face barriers to success that are different from those found in traditional face-to-face courses in four-year universities. Research suggests that motivation and self-regulated learning skills are potentially related to student success in online learning. The preponderance of research on student academic success in online courses is predominantly conducted with traditional, better-prepared students in four-year universities. Yet, there is little research on the effectiveness of online mathematics courses in community college settings with underprepared, nontraditional students. This study examines the relationship of self-regulated learning and academic risk factors to academic performance in community college online mathematics courses. The results of this study indicated that the self-regulation measures of Self-Efficacy for Learning and Performance and Task Value had a statistically significant relationship to academic performance as measured by mathematics final examination scores. Academic risk factors were not found to be predictors of academic performance. The results also indicated that self-regulated learning did not appear to moderate the strength of the relationship of academic risk factors to academic performance. Implications for practitioners are discussed.

Chapter 1: Introduction

Background

Higher education institutions have historically employed a variety of technologies to deliver instruction in innovative ways. Technological capacity for integrating new media systems has evolved over the years and schools have experimented with a variety of technologies such as correspondence, teleconferencing, radio, film, television, digital media, and online learning to provide access, content, and instruction to students (Garrison, 1985).

The promise of many of these new technologies to revolutionize education often faded as technological advances rendered certain innovations obsolete; or in some cases, the educational benefits were simply less than desired (Cuban, 2001). However, online learning, defined in the present study as 80% of course content provided electronically, is firmly established as a recognized instructional delivery format. Indeed, over 28% of all students in public and private higher education institutions now take at least one course online, representing nearly six million students (Allen & Seaman, 2016). Public institutions have consistently maintained that online course offerings are critical to their long-term strategy (Allen & Seaman, 2016).

Within the field of higher education, community colleges are particularly invested in online learning to serve the needs of low-income, immigrant, first-generation, and ethnic minority students (Bailey, Jaggars, & Jenkins, 2015). In 2007, community college students at public institutions participated in online courses relatively more often than those attending other institutions. Twenty-two percent did so, compared with 19% at for-profit two-year institutions, 16% at public four-year, and 12% at private non-profit four-year institutions (Walton, 2011). Considering the total enrollment of all postsecondary students in all higher education institutions, according to a 2011 report, public two-year institutions account for 34.7% of all students enrolled in online learning courses (Walton, 2011). Despite the growing number of online students in community colleges, research on the effectiveness of online learning in community college environments is inconclusive (Shea & Bidjerano, 2016).

Studies evaluating the effectiveness of online learning are often focused on four-year university students who are typically better prepared academically than nontraditional students typically found in community colleges (Jaggars & Bailey, 2010). Proponents of online learning point to a meta-analysis commissioned by the U.S. Department of Education that found student outcomes in hybrid or online courses to be equal to or better than traditional face-to-face courses (Means, Toyama, Murphy, Bakia, & Jones, 2009). However, others argue that such an interpretation is not warranted or applicable to community colleges with traditionally underserved populations (Jaggers & Bailey, 2010). Jaggars and Bailey (2010) pointed out that the meta-analysis included courses that were particularly well-suited to online teaching, for example, computer programming or courses that had additional instructional supports typically provided in face-to-face classes. Understanding the factors that need to be considered for students to be successful in online environments is particularly important for least-advantaged students in community colleges (Cox, 2005).

Among the many critical factors for student success in school, and especially important in the context of online courses, is the ability of students to self-regulate their learning (Bailey et al., 2015; Hodges, 2008). Several theories have been proposed to describe the various elements related to self-regulation in learning environments. Zimmerman (1989) proposed a theory of self-regulation based on Bandura's (1986) developmental social cognition theory. Zimmerman and Martinez-Pons (1990) suggested student efforts to regulate their learning involve three processes: personal, environmental, and behavioral. Moreover, Pintrich and De Groot (1990) argued that self-regulation of cognition and behavior are important aspects of student learning and academic performance. Additionally, motivation plays a critical role in promoting student achievement in that students must actively use their strategies to self-regulate their learning (Pintrich & De Groot, 1990). Self-efficacy, defined as one's belief in one's capabilities, typically with regard to specific tasks, also provides a foundational theory of self-regulation (Bandura, 1977).

The importance of self-regulation as an indicator of academic success in online courses has been sufficiently explored in higher education settings (Agustiani, Cahyad, & Musa, 2016; Barnard-Brak, Lan, & Paton, 2010; Cazan, 2014; Pardo, Han, & Ellis, 2016; Puzziferro, 2008; Xu & Jaggars, 2014). However, there is a dearth of academic research focused on the linkage of self-regulated learning to academic performance in online courses in the community college setting, particularly in mathematics courses.

The present study examines the relationship of self-regulated learning beliefs to academic performance in online mathematics courses in the community college setting. The investigation also explores academic risk factors such as ethnicity, gender, high school graduation status, and age as potential predictor variables to academic success. Finally, the potential for the moderating effect of self-regulated learning on academic risk factors to academic performance is explored.

Statement of the Problem

The ability of students to self-regulate their learning is particularly important in online learning environments where high levels of motivation, self-efficacy, and persistence are thought to be required for success (Jaggars & Bailey,2010; Wijekumar, Ferguson, & Wagoner, 2006). However, a review of literature suggests that self-regulation skills are rarely taught or required as a prerequisite for online courses in community colleges.

Research on the relationship of self-regulated learning beliefs to academic performance with community college students is limited and inconclusive (Cho & Heron, 2015; Puzziferro, 2008). Moreover, some recent research has shown that providing training to students on self-regulated learning strategies potentially improves the academic performance of underprepared students (Bol, Campbell, Perez, & Yen, 2016; Hu & Driscoll, 2013).

College and pre-college mathematics competencies are typical requirements in a community college academic program as conditions of advancement towards a degree or to meet credit requirements to transfer to a four-year institution (Bailey et al., 2015). Online mathematics courses present a particularly challenging barrier for underprepared community college students due to the lack of structure typically found in face-to-face courses such as teacher support and immediate formative feedback (Jaggars & Bailey, 2010). Therefore, the ability to self-regulate potentially plays a key role in online learning success. Understanding the relationship of self-regulated learning and academic risk factors to academic performance can provide teachers and administrators with knowledge to potentially improve student academic success.

Purpose of the Study

The purpose of this study is to examine the relationship of student self-regulated learning beliefs and academic risk factors to academic performance in three community college online mathematics courses: Algebra I, Algebra II, and College Algebra. Students in the present study completed a questionnaire of self-regulated learning beliefs to measure their motivation and self-regulated learning skills. The course final examination mathematics achievement score was the measure of academic performance for each participant. Correlational analyses were conducted to evaluate the relationship of academic risk factors and self-regulated learning factors to academic performance. The study identified the extent to which certain self-regulated learning beliefs moderate the relationship of academic risk factors to academic achievement. Implications for community college administrators and educational researchers are discussed. The study includes a review and critical analysis of research on student academic success in online settings in both community colleges and four-year colleges.

Significance of the Study

Advances in technology and the globalization of the economy are driving the demand for a more skilled and educated workforce (Friedman, 2016). Simultaneously, the current cost (e.g., tuition, fees, room and board) of attending a four-year public university is over $16,000 per year (National Center for Education Statistics [NCES], 2015a). Furthermore, the National Center for Education Statistics (NCES, 2015b) reported a 33% increase in the cost of an undergraduate degree over that past decade making public higher education significantly more difficult to access for nontraditional students. Community college costs are approximately 40% less than public four-year universities (NCES, 2015). Therefore, community colleges serve as an affordable opportunity for nontraditional students to develop the necessary academic skills and knowledge to acquire a degree.

Completing basic mathematics courses is a common prerequisite for qualifying to enter community college career pathways leading to a degree or transfer to a four-year institution (Bailey et al., 2015). Taking online mathematics courses is attractive to nontraditional students who often work or have family obligations requiring a more flexible, accessible learning environment. However, research has shown that the student withdrawal/failure rate in introductory online mathematics classes in community colleges is 25% compared to 12% in face-to-face courses (Jaggars, Edgecombe, & Stacey, 2013). Moreover, students who take online courses compared to face-to-face courses are less likely to persist and attain a degree (Jaggars et al., 2013). Additionally, the performance gap between online and face-to-face courses in community colleges affects a disproportionally number of younger, black males (Xu & Jaggars, 2014). Therefore, students who need to complete mathematics prerequisites in an online setting are significantly disadvantaged compared to students in face-to-face courses. Moreover, the failure to meet mathematics requirements potentially ends their academic career and severely limits their opportunities for good jobs that pay more than $35,000 per year. Research shows that since 1991 the number of good jobs requiring high school diplomas decreased, but the number of good jobs for associate degree holders increased by more than three million (Carnevale, Strohl, & Ridley, 2017).

This study is intended to contribute to the empirical research related to understanding the relationship of student self-regulated learning beliefs to academic performance with community college students taking online mathematics courses. A majority of the research in measuring the effectiveness of online learning is conducted with four-year, better-prepared, traditional university students (Jaggers & Bailey, 2010. This research will focus on nontraditional, often underprepared students and provide new empirical evidence regarding the relationship, or extent of it, of self-regulated learning beliefs to academic performance with community college students.

Secondly, a large number of research studies of online learning evaluate outcomes of short, discrete subjects that are well suited to an online context such as computer science, topic-specific educational interventions, and technology courses. The present study investigates a traditional educational subject (mathematics) conducted over a typical 10-week college course schedule**,** thus making the results potentially more generalizable to a typical community college setting.

Third, many prior studies evaluating the relationship of self-regulated learning beliefs to academic performance do not consider how self-regulated learning beliefs potentially moderate academic risk factors (Bol et al., 2016; Cho & Heron, 2015; Wang, Shannon, & Ross, 2013). This study considers self-regulated learning beliefs as a potential moderating influence on academic risk factors thus providing a more comprehensive picture of the complexities associated with community college student academic success in online mathematics courses.

Limitations of the Study

Several limitations should be considered when interpreting the results of this study. First, the Motivational Strategies for Learning Questionnaire (MSLQ) is based on self-reported measures in that participants are reporting what *they believe to be true* of themselves. These responses may be influenced by the desire to provide answers that are deemed favorable by the researcher (Gall, Gall, & Borg, 2015). Second, students self-select in registering to take online courses. This introduces a potential bias in the sample population of the study. Students who choose to take a course online may have more positive predispositions towards online learning and potentially possess more self-efficacy in their beliefs for success in this learning environment. Third, the study includes only two teachers and three different intact classes at one urban community college. Due to the highly-contextualized nature of online learning, the results of this study should be interpreted with caution and cannot necessarily be generalized to all community college online mathematics courses or any other discipline of study. Finally, the desire to conduct this research in an authentic setting limited the ability to recruit a large number of participants required to obtain statistically significant findings needed to reliably discriminate between alternative hypotheses (Faul, Erdfelder, Lang, & Buchner, 2007).

Definition of Terms

Academic risk factors are demographic characteristics of a student such as gender, ethnicity, age, and high school graduation status that have been associated with potentially influencing academic success.

*Community college*s are public or private two-year postsecondary institutions that primarily award associate degrees and certificates and offer a wide range of services in their local communities (Allen & Seaman, 2016).

Effort regulation is a student’s ability to control focused effort and attention to avoid distractions or uninteresting activities or tasks (Pintrich, Smith, Garcia, & McKeachie, 1991).

Face-to-face typically refers to academic learning environments where the predominant interaction between students and a teacher takes place in-person and in the same room (Allen & Seaman, 2016).

First generation college student is a student whose parents have never attended a postsecondary institution (Peterman, 2000).

Help seeking is seeking help from peers or instructors when needed with a focus on the use of others in learning (Pintrich et al., 1991).

Metacognitive self-regulation is the awareness, knowledge, and control of cognition including planning, monitoring, and regulating activities (Pintrich et al., 1991).

Motivation is comprised of three components: belief about one’s ability to perform a task, goals and beliefs about the importance and interest in the task, and emotional reaction to the task (Pintrich et al., 1991).

Nontraditional students are students with demographic characteristics different from typical college students entering postsecondary education directly from high school. They tend to be older, potentially working full-time or part-time, possibly with family responsibilities, may require financial support, and potentially lacking success in high school (Bailey et al., 2015).

Online learning is a course where most (more than 80%) or all of the content is delivered online. Typically, there are no face-to-face meetings (Allen & Seaman, 2016, p. 7).

Self-efficacy is the belief in one's capabilities to organize and execute the courses of action required to manage prospective situations. Self-efficacy is derived from four principle sources: performance accomplishments, vicarious experience, verbal persuasion, and psychological and affective states (Bandura, 1986).

Self-efficacy for learning and performance refers to a student's expectations of performance and the judgment about one's ability and confidence to accomplish a task (Pintrich et al., 1991).

Self-regulated learning refers to the self-directed processes and self-beliefs that enable learners to transform their mental abilities into an academic performance skill. It is a proactive process that students use to acquire an academic skill such as setting goals, selecting and deploying a strategy, and self-monitoring their effectiveness (Zimmerman, 2008).

Task value is the student's evaluation of a task in terms of how interesting, important, or useful it is (Pintrich et al., 1991).

Time management is using time well and having an appropriate place to study (Pintrich et al., 1991).

Underprepared students are students who fail to meet an institution's standards for college readiness (Bailey et al., 2015).

Research Questions

1. What is the relationship of self-reported, self-regulated learning beliefs to academic performance, as measured by final examination score, in an online learning environment?

2. What is the relationship of selected academic risk factors to academic performance, as measured by final examination score, in an online learning environment?

3. To what extent do self-regulated learning beliefs moderate the relationship of academic risk factors to academic performance?

Research Hypotheses

H1. Students with higher self-regulated learning beliefs will achieve significantly higher academic performance, as measured by final examination score, than students with lower self-regulated learning beliefs.

H2. Students with personal characteristics associated with academic risk factors will achieve significantly lower academic performance, as measured by final examination score, than students with personal characteristics not associated with academic risk factors.

H3. Self-regulated learning beliefs will significantly moderate the relationship of academic risk factors to academic performance.

Chapter 2: Literature Review

Introduction

This literature review presents research related to the topics, relevant theoretical constructs, and the specific questions posed in this study. The topics covered are: historical perspective and theories associated with distance education, trends and growth of online learning in higher education, theoretical constructs of self-regulated learning and its relationship to academic performance, the community college learning environment, and the role of remedial mathematics in community colleges.

Distance Education

Historical Beginnings and Theories

The concept of distance education is fundamentally defined by the separation of students and teachers by distance and sometimes by time (Moore & Kearsley, 1996). This separation necessitates an artificial communication medium to deliver information and provide for interaction between teacher and students (Moore & Kearsley, 1996). Distance education was initially dependent on print-based materials to deliver course content. Today, distance education is dependent on electronic media as the primary means of communication and content delivery.

Charles Wedemeyer, considered by many to be the "father of modern distance education" (Diehl, 2013), described distance education in terms of a student's ability to study independently apart from the instructor's presence. Wedemeyer's definition was centered on the teaching-learning arrangement where the teacher and learner carry out their tasks and responsibilities apart from one another. Wedemeyer founded the Articulated Instructional Media (AIM) project, which created an integrated approach to the use of media for educating mature learners (Saba, 2013). Wedemeyer created a systems approach to course design made up of instructional designers, technology specialists, and content experts (Diehl, 2013). Wedemeyer's work influenced the emergence of the British Open University, a fully autonomous, degree-granting institution, and a worldwide leader in distance learning (British Open University, 2017; Moore & Kearsley, 1996).

Moore (1972), building on Wedemeyer's independent learning theory, introduced the "Theory of Transactional Distance" which included learning attitudes, psychological characteristics, and independence of the learner. Moore's (1972) theory was stated as:

> distance education is not simply a geographic separation of learners and teachers, but importantly, is a pedagogical concept. It is a concept describing the universe of teacher-learner relationships that exists when the learners and instructors are separated by space and/or time. (Moore, 1972, p. 22)

Moore (1972) set forth the key constructs of distance education as structure, dialogue, autonomy, and transactional distance. Saba and Shearer (1994) eventually demonstrated the validity of the relationship between dialogue and structure related to transactional distance. The theory can be summarized as: when structure increases, transactional distance increases and dialogue decreases (Saba & Shearer, 1994).

Saba (2013) pointed out that many researchers in the field of distance education are not familiar with foundational theories associated with distance education and therefore lack a holistic approach to an understanding of this field of study. The following summarizes the development of the original constructs and theories that were empirically verified for describing distance education.

The term “distance” in education was originally defined as the construct of transactional distance measured by dialogue and structure (Saba, 2013). Saba (2013) argued that modern distance education modes such as online learning or web-based learning require similar, rigorous validation in order to be taken as serious constructs. Saba (2013) pointed out that practitioners face three challenges required to grow the theoretical base of distance education. First, the need for consistent terminology. The proliferation of acceptance of poorly defined terms and phrases in the current literature impedes the ability of researchers to build a consistent base of a unified paradigm. Second, the lack of historical perspective. Saba (2013) argued that for some researchers the historical perspective on distance education begins when they become interested. Third, the absence of construct validity. Terms such as e-learning or online learning lack the empirical test of validity. These challenges illuminated by Saba (2013) are evident in the current approach of implementing online learning in community colleges. Cox (2005) argued that the proliferation of online learning in community colleges lacks empirical evidence and is often driven by myths and the perceived need to stay competitive. A detailed analysis of the research conducted by Cox (2005) regarding these myths is included in this literature review. Defining distance education as a construct is an important step in developing an empirical basis for this instructional strategy.

Keegan (1980) defined six components of distance education as: 1) separation of teacher and student, 2) influence of the educational institution, 3) use of technical media, 4) provisions for two-way communication, 5) the possibility of occasional seminars, and

6) participation in the most industrial form of education. These early descriptions of distance education sufficed to define this teaching-learning relationship given the technologies and affordances of the time. As technology advanced the definition of distance education required updating, but the foundational premise of this mode of learning remained constant.

The important constructs in distance education that are relevant to this research paper are the concepts of control and independence. Garrison and Baynton (1987) developed the idea that the greater degree of student self-direction in deciding what to learn, how to learn, or to what extent to learn, the less the instructor has control. They posited: “Control is not achieved by simply providing independence or freedom from outside influence. It is the dynamic balance among these three components that enables the student to develop and maintain control over the learning process” (Garrison and Baynton, 1987, p. 5).

Control, as defined by self-regulated learning, will be explored in greater depth in the present study. Keegan (1980) and Sumner (2000) posited that technology plays an important role in the evolution of distance learning. I will next discuss how technology has influenced and changed distance learning.

The Technical Evolution of Distance Education

Technology plays a significant role in distance education in that it mediates the separation between the teacher and student using a variety of print, electronic, and audiovisual mediums (Sumner, 2000). Garrison (1985) described the evolution of distance education as having three distinct generations of technological innovations: correspondence, telecommunications, and computers. Each generation provided new affordances to improve upon the two-way communication between teacher and student as well as student to student.

Correspondence education consisted of print-based materials sent through the U.S. Postal Service, dating back to 1833 (Baath, 1985). This method of delivery provided educational opportunities for generations of people at a very low cost and served as the primary medium of distance education in postsecondary institutions in the United States (Pittman, 2013). However, the delay in response between teacher and student placed a large burden on the student to be self-sufficient and motivated to complete the course requirements (Garrison, 1985).

Telecommunications, typically wire, telephone, television, or radio electronic communication, were built upon the print-based system of correspondence and improved upon the model with some mediums such as telephones providing more immediate two-way communication between teacher and student (Garrison, 1985). However, the scalability of such a system to provide access to great numbers of students was significantly constrained. Moreover, the flexibility of time was further constrained requiring students and teachers to communicate during defined times. The limitations of these communications systems were transformed with the introduction of the personal computer in the 1980s.

Computers, when introduced as a new means of distance education communication in the 1980s, offered potential to increase both interaction and independence for students. “Computer Assisted Learning” was a promising technology that could potentially efficiently mediate the interaction between human and machine

(Kearsley, Hunter, & Seidel, 1983). Garrison (1985) posited that learners could maintain complete independence while maximizing two-way communication with the teacher.

Adding to the promise of computer-assisted learning and aligning with social learning theory, Grice (1989) developed the cooperative principle. This principle stated that the listener and speaker in a social context have an implicit agreement of interest given the speaker is trying to make sense by being informative, accurate, relevant, and concise. The “speaker,” in the context of a computer-assisted learning environment, is the multimedia messages delivered by the computer. Activating a social response in a computer-assisted learning environment increases the desire of the learner to make meaning by selecting, organizing, and integrating the content (Mayer, 2014). Additionally, technology made possible student-to-student interaction in learning environments, which further increased the potential for social interaction.

Computer-assisted-learning, while holding promise, was not accepted by all researchers. Daniel (1983) expressed deep concerns about the opportunities and threats these “stand-alone systems” presented. Daniel (1983) argued that the political and technological trends in the 1980s would decrease government spending on education and increase autonomous learning. Daniel (1983) also noted the increased interest in education as a means for training for employment, rather than university-level academic work. However, distance education in the modern era has advanced well beyond “stand-alone systems” and now provides new methods and means to deliver instructional content via connected computers on the Internet.

Distance Education in the Modern Era

In 1994, the National Research Council released a report that set the parameters for privatization of the Internet (Internet Society, 2013). This led directly to the advent of the modern Internet and the World Wide Web and opened the floodgates for education institutions and private enterprises to begin building educational platforms accessible to vast numbers of students. Public higher education institutions, primarily community colleges, also took advantage of grants from the Alfred P. Sloan Foundation to begin building online course offerings in 1992 (Online Learning Consortium, 2017). The Sloan Foundation, recently renamed the Online Learning Consortium, has continued to fund and promote research into the effectiveness of distance education for over two decades (Online Learning Consortium, 2017). While distance education is still fundamentally defined by the two-way communication between a teacher and student, innovations in technologies to produce, organize, communicate, and distribute instructional content radically changed this relationship and enabled new ways for interactivity such as videoconferencing, screen-sharing, and adaptive learning systems. As these new computer affordances continue to evolve, researchers need common terms to define and analyze varying contexts of how distance education is applied to instructional practices.

A common set of definitions to define and describe distance learning has been elusive (Saba, 2013). Saba (2013) pointed out that education researchers poorly defined or under-defined the permutations of distance education modes. A survey conducted in 2010 identified "conflicting responses" to the wide variety of terms used to describe distance education (Moore, Dickson-Dean, & Gaylen, 2010). Allen and Seaman (2016), in their annual report card on online learning, provided a useful working definition of four common modes of learning: traditional or face-to-face, web-facilitated, blended/hybrid, and online. For the purposes of this paper, and to provide clarity, Allen and Seaman's (2016) working definitions will be used:

Traditional or face-to-face: A course where no online technology is used and content is delivered in person, in writing, or orally (Allen & Seaman, 2016, p. 7).

Web-facilitated: The proportion of content delivered online ranges from 1 to 29%. A course that uses web-based technology to facilitate, what is essentially, a face-to-face course. It may use a learning management system (LMS) or webpages to post the syllabus and assignments (Allen & Seaman, 2016, p. 7).

Blended/hybrid: The proportion of content delivered online ranges from 30-79%. A course that blends online and face-to-face delivery. A substantial proportion of the content is delivered online, typically uses online discussions, and typically has a reduced number of face-to-face meetings (Allen & Seaman, 2016, p. 7).

Online: The proportion of content delivered online is greater than 80%. A course where most or all of the content is delivered online either synchronous or asynchronous. Typically, no face-to-face meetings (Allen & Seaman, 2016, p. 7).

As the Internet began growing at a rapid pace, institutions of higher education saw opportunities to provide students with flexible, affordable course offerings. The publicity and promise around "Massive Online Open Courses" (MOOCs) compelled major education institutions to consider offering online courses to stay relevant and competitive (Pappano, 2012). While the enthusiasm for the promise of MOOCs has waned, online courses continue to play a strategic role in standard course offerings in higher education (Allen & Seaman, 2016).

Online Learning

Trends in Growth and Enrollment

The proliferation of connected digital devices, combined with universal access to educational content on the Internet, has made possible new platforms with respect to how education is delivered and consumed. Online learning, previously defined as having at least 80% of content delivered online, some materials provided in hardcopy, and with no face-to-face meetings now utilizes newer technologies to deliver content for teaching and learning (Allen & Seaman, 2016).

A recent study tracking online course usage in higher education in the United States reported that 31.6% of all college students, over six million students, are presently taking at least one course online, which is a significant increase in enrollment from 2014 with 14.5% taking at least one online course (Seaman, Allen, & Seaman, 2018; NCES, 2014). Of the students taking online courses, 67% do so at a public institution (Allen & Seaman, 2017). Importantly, online education enrollments remain highly concentrated in a relatively small number of institutions comprising almost half the students in just five percent of the institutions (Seaman et al., 2018). The University of Phoenix-Arizona is by far the largest private for-profit institution with 131,629 total enrollments (Seaman et al., 2018).

There are important differences between large and small institutions of higher education regarding the attitudes and practices of online learning. In 2015 only 46% of small institutions (less than 3,000 students) responded that online learning is a critical part of their long-term strategy, a drop from 70.2% in 2014 (Allen & Seaman, 2016). However, these institutions only represent 2.1% of all college students. Additionally, public institutions, which began offering online courses and programs sooner than private institutions, have consistently maintained that online learning is critical to their long-term strategy (Allen & Seaman, 2016). However, recent trends in total student enrollment at U.S. higher education institutions has declined by 3.8% between 2012 and 2016 (Seaman et al., 2018). Moreover, the enrollment declines have been uneven with private for-profit institutions accounting for all of the loss of students, while private non-profit and public institutions both had slight increases in enrollment during the four-year time period (Seaman et al., 2018). The reasons for enrollment declines could be related to the cost of attending college, potentially putting more pressure on colleges to reduce overhead by providing more cost-effective online courses. Given that these larger public institutions serve different populations of students, the pattern of shifting the emphasis towards online courses from face-to-face courses could have implications for the academic success of certain students. These institutions might potentially assume that online learning is equally as effective as face-to-face learning based on the U.S. Department of Education meta-analysis which found that "students who took all or part of their classes online performed better, on average, than those taking the same courses through traditional face-to-face instruction" (Means et al., 2009, p. xiv).

Effectiveness of Online Learning in Higher Education

As online learning continues to grow as a mode of instructional delivery, administrators and teachers seek to understand the effectiveness of online or hybrid/blended learning courses compared to traditional, face-to-face learning. The research on the effectiveness of these various modes of content delivery generally measures student academic achievement as the primary dependent variable. Researchers have investigated the effectiveness of online learning compared to face-to-face learning and found inconclusive outcomes or little difference in student achievement (Bernard et al., 2004; Jaggars & Bailey, 2010; Xu & Jaggars, 2014).

Bernard et al. (2004) conducted a meta-analysis of 232 studies between 1989-2002 and looked at achievement, attitude, and retention outcomes of online courses compared to face-to-face courses and found no meaningful differences in effect sizes with wide variability with all three measures. The investigators concluded that the most important finding was the wide range in effect sizes in achievement outcomes with effect sizes ranging from -1.31 to +1.41 (Bernard et al., 2004). However, the mean achievement effect sizes comparing online synchronous courses favored face-to-face courses, while the asynchronous online course outcome favored online courses over face-to-face courses. Bernard et al. (2004) surmised that synchronous learning is a poor-quality replication of traditional classroom learning in that it lacks the flexibility in scheduling and also lacks the individual attention generally available in asynchronous courses. Additionally, while prior studies compared various media to face-to-face courses, Bernard et al. (2004) compared only general distance education course outcomes to face-to-face outcomes. This research appears to support Keegan’s (1980) defining notion of proximity of teacher and student as the primary independent variable assuming media use is consistent in both settings.

Conversely, proponents of online learning were encouraged by a meta-analysis commissioned by the U.S. Department of Education that found, on average, students performed better in online learning conditions than students in face-to-face classes (Means et al., 2009). The study considered more than one thousand empirical studies of online learning student outcomes compared to face-to-face conditions. A screened set of 51 independent effects was analyzed and found showing that students in online courses performed better than those in face-to-face instructional settings, with an average modest effect size of +0.24, $p < .01$. However, the study noted numerous limitations such as: small sample sizes, failure to report retention rates, and in many cases, potential author biases. Despite the evidence that online learning can be effective, the meta-analysis did not clearly demonstrate that online learning is superior as an instructional mode over face-to-face instruction (Means et al., 2009). The researchers pointed out that online courses often included additional learning time, more materials, and extended opportunities for collaboration which likely produced the observed learning advantages of online courses (Means et al., 2009).

Similar support for online learning was found in a subsequent meta-analysis commissioned by the U.S. Department of Education in 2013, which considered 50 studies contrasting online or hybrid courses with face-to-face courses. This study differed from the prior U.S. Department of Education meta-analysis of the effectiveness of online learning in that it only considered web-based learning**,** eliminating audio, telecourses, and stand-alone computer-based instruction (Means, Toyama, Murphy, & Bakia, 2013). The finding of this meta-analysis was that purely online and hybrid courses produce stronger student learning outcomes compared to learning in traditional, face-to-face learning environments. The mean effect size for all 50 studies was .20, $p < .001$ (Means et al., 2013). However, the mean effect size for 27 purely online studies compared to face-to-face conditions was not statistically significant. The mean effect size for the 23 hybrid courses versus face-to-face instructional settings was statistically significantly different, with an effect size of +0.35, $p < .000$ (Means et al., 2013).

Another study comparing online learning to face-to-face learning outcomes addressed the inherent selection bias associated with online learning enrollment. Stack (2015) conducted a quasi-randomized experiment comparing online learning outcomes with face-to-face courses and found no statistically significant differences in achievement. The study was unique in that it took advantage of an administrative error which failed to list a section of a course as being online. The students who discovered they were in the online class remained as did the students who were registered in the face-to-face section. This allowed the study to address two recurring limitations of research in online versus face-to-face environments: selection bias of course delivery mode and exam proctoring (Stack, 2015). Both courses were taught by the same instructor, utilized the same materials, and all examinations were proctored, in person, by the same instructor. Stack (2015) found no significant difference in academic performance between online and face-to-face instructional modes (.147, $p > .05$). Additionally, the students' perception of instruction quality did not differ by instructional mode. However, the relatively small sample size (64) and the non-random assignment of students raises a potential threat to external validity.

The research comparing the effectiveness of online learning and face-to-face learning is dominated by "media comparisons" and often ignores other factors that potentially influence the effectiveness of online learning (Means et al., 2009, 2013 Stack, 2015). Seeking to expand on the research on the effectiveness of online learning, Zhao, Lei, Yan, Lai, and Tan (2005) examined 51 journal articles and evaluated pedagogical and technological factors that potentially differentiate student learning outcomes in online learning courses. This meta-analysis conducted by Zhao et al. (2005 found that not all online learning education programs are equal. In fact, Zhao et al. (2005 found the following factors to be significant moderators of student academic outcomes: studies published after 1998 found online learning to be significantly more effective than face-to-face learning (d = .20, p < .001); studies where the author of the article was also the online instructor found the outcome significantly favored online learning (d = .33, p < .001); high instructor involvement in an online course was the most significant moderator to student outcomes (d = .21, p < .001); computer science courses showed a significant difference in favor of online learning student outcomes compared to face-to-face (d = .50, p < .01); the type of interaction online between the instructor and the student (synchronous and asynchronous) was a significant predictor of academic performance if both means of interaction were employed (d = .49, p < .01). However, instructor involvement as a researcher in the study carries with it conflict of interest potential.

While the empirical evidence analyzing the effectiveness of online learning appears to be inconclusive, Zhao et al.'s (2005) research suggests that specific elements in course design, instructor presence, technology integration, and context can be critical factors in student academic success in online learning. Another important consideration of the present study is the relationship of self-regulation and academic performance in online learning. The next section will explore the theoretical foundations of self-regulated learning, the empirical research on the role of self-regulated learning in online environments, and research related to the teaching of self-regulation skills.

Self-Regulated Learning

Theoretical Foundations

Self-regulated learning is a term used to describe the degree to which students are metacognitively, motivationally, and behaviorally active participants in their own learning process (Zimmerman, 1989). Self-regulated learning involves the self-directive processes and self-beliefs that enable learners to transform their mental abilities into academic skill performance (Zimmerman, 2008).

Cognition and behavior are important aspects of self-regulation with respect to student academic performance (Pintrich & De Groot, 1990). Pintrich and De Groot (1990) described self-regulated learning as consisting of three important components for classroom performance: metacognitive strategies for planning, modifying, and monitoring cognition, students' management and control of their efforts on academic tasks, and cognitive strategies students use to learn, remember, and understand academic material.

Self-regulation is rooted in social cognitive theory in that behavior is motivated and regulated by self-influence (Bandura, 1991). Bandura (1991) further posited that self-regulation is also linked to self-efficacy, which plays an important role in one's belief in one's thoughts, motivation, and actions. Bandura's (1991) self-efficacy theory is derived from four principles that guide beliefs in one's capacity to organize and execute a successful course of action required for a particular situation. First, prior success in performance accomplishments. Second, observation of a role model through a vicarious experience. Third, encouragement of a credible and competent other through verbal persuasion. Finally, a psychological and affective arousal state that impacts one's belief in turning self-efficacy thoughts into action - a key to self-regulation.

While knowledge of cognitive and metacognitive strategies is often required for student success, students must be motivated to act. Motivational theory is adapted from the general expectancy-value model of motivation (Wigfield & Eccles, 2000). Motivation plays a significant role in self-regulated learning. Three components of motivation are linked to self-regulated learning: a) expectancy in the belief to perform a task, b) a value component related to the importance or interest in the task, and c) an affective component which includes a student's emotional reaction to a task (Pintrich & DeGroot, 1990). The next section will examine the empirical research associated with the relationship of self-regulation with academic performance in online learning environments.

Self-Regulation and Academic Performance in Online Learning

Self-regulated learning is regarded as an important competency mediating the academic success of students in most learning environments (Zimmerman, 2008). Online learning environments are significantly different from conventional learning environments in that students and teachers are not physically present together and students are more responsible for their own learning (McMahon & Oliver, 2001). Numerous researchers have investigated the relationship of various self-regulated learning beliefs to academic performance and found that self-regulation does have a relationship to academic performance (Pintrich et al., 1991; Puzziferro, 2008; Wang et al., 2013). However, the empirical research on the relationship between self-regulated learning and academic performance in online environments often includes other variables such as course satisfaction, previous experience with online learning, and technology self-efficacy as additional variables to consider in developing a comprehensive understanding of the factors attributed to student academic performance (Cho & Heron, 2015; Wang et al., 2013). While there is evidence that self-regulated learning beliefs do influence academic performance, the evidence suggests that only certain self-regulated learning beliefs, in limited contexts, can explain a statistically significant amount of the relationship to academic performance.

Puzziferro (2008) analyzed the academic performance of 815 community college students enrolled in a random sample of 163 liberal arts online courses. The study examined performance as a function of grade and course satisfaction as well as measured self-efficacy for online technologies and self-regulated learning strategies. Puzziferro (2008) found that time and study environment and Effort Regulation were significantly related to academic performance in online undergraduate courses. Using Pintrich and DeGroot's (1990) theory of self-regulated learning, Puzziferro (2008) measured cognitive learning strategies using the Motivated Strategies for Learning Questionnaire (MSLQ). The study revealed significant differences in mean scores by final grade for time and study environment $F(4, 810) = 4.41$, $p = .00$ and for Effort Regulation $F(4,810) = 5.46$, $p = 0.00$. Additionally, the self-regulation learning beliefs of rehearsal, elaboration, Metacognitive Self-Regulation, and time and study environment were found to be significantly positively correlated with course satisfaction. The study also included a measure of online technologies self-efficacy but found no significant correlation with student academic performance. A limitation of this study was the use of grades as the measurement of academic performance, which can be inconsistent and unreliable as a measure of actual learning in a course. The unique contribution of this research was the inclusion of course satisfaction and the role of online technology self-efficacy as variables to further explain academic performance along with the relationship of self-regulation beliefs.

Wang, Shannon, and Ross (2013) conducted a similar study as Puzziferro (2008) but with a very different student population. They simultaneously measured personal characteristics, technology self-efficacy, and self-regulation beliefs to understand the relationship to course academic outcomes and satisfaction. They examined 256 undergraduate students taking online courses at a major university. Results of the study confirmed Puzziferro's (2008) findings that self-regulated learning is a significant predictor of course satisfaction and performance. Wang et al. (2013) also considered technology self-efficacy, course satisfaction, and previous experience with taking online courses in their study. The researchers found that students with more prior online learning experience tended to demonstrate more effective learning strategies and report stronger levels of motivation resulting in higher grades. However, this finding might suggest that the self-selection process bias, where students who are successful in an online course(s) continue, while those who have disappointing experiences early on do not, plays a role. The results of this study further confirm that numerous factors combine to predict academic performance in online learning environments.

In research germane to the present study, Cho and Heron (2015) measured the motivation and learning strategies of 229 college students enrolled in online remedial mathematics courses. The students used the courseware ALEKS as their primary source to learn the course material. In addition, the students were offered twice a week in-person class sessions as additional support. They found that Self-Efficacy for Learning and

Performance was the only motivational variable that significantly predicted final grades as measured by a comprehensive final examination $\beta = .36$, $p < .01$ (Cho & Heron, 2015). However, the study found that the learning strategies of metacognition, self-regulation, and critical thinking were not predictors for academic success. The study included measuring emotional variables along with motivational variables and predicted 63.1% of the variance in course satisfaction. This finding is consistent with Wang et al.'s (2013) finding that course satisfaction is related to course achievement. However, it is important to note that Cho and Heron (2015) measured achievement with a final examination score while Wang et al. (2013) used course grades to measure achievement. Using course grades does not always reflect true achievement due to the potential for subjective bias in grading. Moreover, the study concluded that only Self-Efficacy for Learning and Performance was a significant predictor of achievement, thus supporting Bandura's (1986) and Zimmerman's (2000) social cognitive view of learning. The finding that emotion played a significant role in an online course setting further supports the notion that understanding success in online courses is multidimensional.

Augustiani, Cahyad, and Musa (2016) also found evidence of the positive relationship between Self-Efficacy for Learning and Performance and academic performance. Augustiani et al. (2016) conducted a correlational study with 101 students in an undergraduate psychology course to examine the relationship between self-efficacy, self-regulation of learning, and academic achievement. Academic achievement was measured using end of semester grades. The students completed two self-report surveys to measure: 1) academic self-efficacy and 2) self-regulation using selected subscales of the MSLQ questionnaire (metacognition, Effort Regulation, time management, and peer learning). Agustiani, Cahyad, and Musa (2016) found that self-efficacy, self-regulated learning, and academic achievement were positively and significantly correlated. Self-efficacy had a small but significant positive relationship with academic performance with a Pearson's correlation coefficient, 0.263, $p < 0.01$ and self-regulated learning had a small, positive significant relationship with academic performance 0.394, $p < 0.01$. The hypotheses that better self-regulation and stronger self-efficacy would lead to higher academic achievement were supported.

Lynch and Dembo (2004) investigated the relationship of self-regulation skills as predictors of academic success in a blended learning context. Prior research reviewed in this paper was contextualized in fully online courses. Additionally, this research used the independent variable of verbal ability as a covariate. The research included 94 students in an undergraduate marketing class at a four-year university. Four self-regulation subscales from the MSLQ questionnaire were selected as independent variables to predict academic success: intrinsic goal orientation, Self-Efficacy for Learning and Performance, time and study environment management, and help seeking. The self-belief of Internet self-efficacy was also measured. The researchers found that only Self-Efficacy for Learning and Performance and verbal ability made significant contributions to predicting variance on grades (Adjusted R Square value = .115, F (2,91) 7.06, $p < 0.05$). The blended instructional mode of the course and the inclusion of embedded self-regulation enhancing elements also contributed to the findings that self-regulation was not problematic for this population. As will be discussed later in this paper, community college students face considerable disadvantages in most online learning environments due to their lack of self-regulation learning skills and low self-efficacy for learning. This study exemplifies the bias in research measuring self-regulated learning in that the students were highly self-regulated, attended a well-regarded university, and underwent a rigorous selection process for inclusion in the study. The results of this study also supports prior research findings that Self-Efficacy for Learning and Performance is a significant predictor of academic performance (Cho & Heron, 2015; Pintrich et al., 1991). The positive correlation of verbal ability to academic performance is an important consideration given that online courses are generally text-based and require verbal skills to read and comprehend material to be successful. Lynch and Dembo's (2004) findings suggest that nontraditional students lacking verbal skills are potentially disadvantaged in online courses. The next study in this literature review considers the effects of providing students with support for self-regulation in an online developmental mathematics course.

McClain (2015), in a dissertation employing a quasi-experimental design with 661 students, investigated the effects of using a self-monitoring instrument on academic achievement, self-regulated learning levels, and course grade in an online postsecondary developmental mathematics course. The results indicated a small but statistically significant increase in self-regulation for those students who utilized the self-monitoring instrument. A significant interaction effect was found and a subsequent t-test found that the experimental group exhibited significantly higher levels of self-regulated learning $t(218) = -2.96$, $p = .003$, indicating that having at least one experience of completing a self-monitoring record significantly increased the students' level of self-regulated learning over time. When considering mathematics achievement, the data showed that the experimental group, as a whole, had higher mean examination scores than the control group. The transformed and adjusted mean scores and results of the ANCOVA revealed that this difference was statistically significant at the level $p < .01$ when comparing the control group and experimental group as a whole. However, there was a very small effect size of .01 (McClain, 2015). McClain also documented a correlation between self-reported self-regulation levels and final course grade. While the McClain (2015) study did show promise of the positive relationship of using a self-monitoring tool to self-regulated learning levels and academic achievement, the Online Self-Regulated Learning Questionnaire (QOSL) survey instrument used was modified for this particular study, calling into question the validity and reliability of the instrument, neither of which was reported by the author. Moreover, while differences were found to be significant, effect sizes were very small and likely not impactful. Research suggests that self-regulated learning beliefs are potentially significantly and positively related to academic performance (Agustiani et al., 2016; Cho & Heron, 2015; Lynch & Dembo, 2004; Puzziferro, 2008).

A common measure of student self-regulation is based on self-reports using the MSLQ questionnaire survey. Some researchers, rather than survey existing self-regulation beliefs, have conducted quasi-experimental studies to investigate if self-regulation skills can be taught and the subsequent relationship to academic outcomes. This next section will explore empirical research related to the effectiveness of teaching and supporting self-regulation.

The Effectiveness of Teaching Self-Regulation

Research suggests that self-regulation potentially plays a role in academic success (Pintrich et al., 1993; Puzziferro, 2008). Empirical studies measuring the effect of self-regulation learning interventions suggest that providing support for self-regulation skills fosters statistically significant higher academic outcomes (Rowe & Rafferty, 2013). Rowe and Rafferty (2013) identified two categories of self-regulation interventions that have been researched: prompting and training. Prompting is guiding and supporting students in self-regulation activities, such as metacognition, while in the process of learning. Training is explicit instruction on the skills of self-regulation such as help seeking, time management, and goal setting.

Zheng (2016) conducted a meta-analysis in which he examined 26 research papers and 2,648 students on the effects of self-regulated learning scaffolds on academic performance in computer-based learning environments. The analysis indicated that self-regulated learning scaffolds generally produced moderately significant positive effects on academic performance (ES = 0.438). Scaffolds can be categorized based on different functionalities such as conceptual, metacognitive, procedural, and strategic considerations (Hannafin, Land, & Oliver, 1999). Scaffolds such as tools, strategies, prompts, metacognitive feedback, or guides were analyzed. The findings suggest that scaffolds must support the whole process of self-regulated learning from defining tasks, setting goals, making plans, enacting tactics, and adapting metacognition. Studies that measured multiple scaffolds had the highest effect size (ES = .5777). Additionally, domain specific scaffolds and adaptive scaffolds that adjust based on students’ learning needs can lead to better academic performance.

Bol, Campbell, Perez, and Yen (2016) conducted a quasi-experimental study investigating the effects of training in self-regulation on metacognition and math achievement. The participants were 116 community college students enrolled in 16 intact face-to-face instruction courses. Students were randomly assigned to the treatment and control groups. Participants in the treatment group completed four self-regulated learning exercises based on Zimmerman's (2002) cyclical model. The MSLQ questionnaire survey was used to measure pre and post self-regulation beliefs of Metacognitive Self-Regulation and time/study environment skills. Bol et al. (2016) found significant differences between the two groups suggesting that training in self-regulation can improve self-regulation beliefs. Additionally, t-tests indicated significant improvements in mathematics achievement scores between the two groups as measured by final examination results using the MyMathLab software $t(70,90) = -2.60$, $p = .011$ (Bol et al., 2016).

In a related study to investigate the role of metacognition in learning, Kauffman, Ge, Xui, and Chen (2008) conducted a quasi-experiment to explore the self-regulation processes of metacognition and reflection to understand how automated instructional support using prompts influenced problem solving and writing. The sample included 54 undergraduate students in an intact educational psychology course at a large university. Students were randomly assigned to a 2x2 design with students in one group receiving scaffold prompts to assist with problem solving, while another group received prompts associated with reflective practice. A pre-test of academic self-efficacy and self-reported metacognitive self-awareness was also conducted. Students were assessed on their written responses to problems in a case study. Results indicated that students provided with prompts for problem solving scored higher on their case study evaluation and wrote with more clarity than those students who did not receive prompts. However, students prompted to reflect on their work produced better outcomes only if they were also prompted during the problem-solving period of their assessment (Kauffman, Ge, Xui, &

Chen, 2008). The researchers surmised that the problem-solving prompts served to clarify the assignment goals and promoted self-monitoring - both important skills of self-regulated learning.

Chang (2007) conducted a quasi-experiment to investigate the effects of a self-monitoring strategy and motivational beliefs in an online language course. Participants were 99 college freshmen enrolled in an intact English class at a university in Taiwan. The intervention included a self-monitoring recording form where students were asked to record their starting time, place they studied, and persons they studied with. They were also asked to predict their after-lesson quiz score. Following the quiz, they were asked to record their quiz score, logout time, and note any distractions they encountered during their study time. Motivational beliefs were measured with the MSLQ questionnaire utilizing the subscales of Self-Efficacy for Learning and Performance and learning beliefs. Chang (2007) found that students who employed the self-monitoring strategy scored higher on the course tests and motivational beliefs than those in the control group. Higher-level English proficiency groups obtained higher scores on both measures, but the difference was not statistically significant. However, the lower-level English proficiency group students performed statistically significantly higher than a control group on both academic performance and motivational beliefs. The results of the study revealed a significant main effect of self-monitoring on academic performance. This study also demonstrated that when providing tools or prompts that foster self-regulation, these tools can potentially play an important role in academic outcomes. The specific context of this study has limited generalizability but nevertheless provides more empirical support for self-regulated learning interventions. The empirical evidence suggests self-regulation has a relationship to academic outcomes. I will next examine the specific learning environment of community colleges to examine the empirical evidence of self-regulation in online learning, and in particular, with online remedial mathematics courses.

Community College Learning Environment

Role in Higher Education

In 2015 there were over 17 million undergraduate students enrolled in degree-granting postsecondary institutions in the United States (NCES, 2015b). Of those students, 10.5 million (62%) attended four-year universities while 6.5 million (38%) attended two-year institutions. The two-year institutions, commonly referred to as "community colleges," play a significant role in educating postsecondary students in the United States. There are currently 1,563 two-year institutions with more than 80% of those representing public colleges (NCES, 2015b).

The distinction between four-year universities and community colleges lies in the mission of the schools, programs offered, tuition costs, and degrees granted. Community colleges generally focus on providing a narrow range of career-oriented programs at the certificate and associate's degree levels and courses which prepare students for transfer to four-year institutions. Four-year institutions offer a broad range of academic programs leading to bachelor's degrees (Carnegie, 2015).

Another key distinction of community colleges is with admissions policies. In 2015, 98% of public two-year institutions offered open admissions, meaning they accepted all applicants. This is contrasted with 19% of public four-year institutions that offered open admissions and 16% of private non-profit institutions that offered open admissions. Open admissions is a critical factor in providing access and equity to education regardless of economic status, ethnicity, or academic records (NCES, 2015b). Open admissions is certainly a critical consideration for many nontraditional students seeking to enter higher education. However, the cost of the education is also a paramount consideration.

Costs to attend a community college are significantly less than public or private four-year universities. Average cost (tuition, fees, books, supplies, room & board) in 2015 to attend a community college full-time and live on campus was $9,337 annually compared to $19,217 for a public four-year institution and $45,951 at a private four-year institution (NCES, 2017).

Characteristics of Community College Students

Community colleges serve a disproportionate number of older, low-income students representing non-white, often first-generation students (Provasnik & Planty, 2008). Compared to their counterparts at four-year universities, community college students are less likely to be prepared for their academic studies and less likely to aspire to or earn a degree (Yu, 2017). In 2004, nearly 40% of community college students were financially dependent (i.e., under 24 years old and financially dependent on their parents), 26% were financially independent of their parents, 20% were independent and married with children, and 15% were independent, single parents (Horn & Nevill, 2006). Compared to students attending four-year universities, community college students tend to be older, female, and lower-income, as well as comprise larger proportions of students of color (American Association of Community Colleges [AACC], 2018; Horn & Nevill, 2006). Hispanics are the fastest-growing population in community colleges representing 22% of total enrollments (AACC, 2016). While there is an abundance of empirical research on the effectiveness of online learning in four-year institutions with capable students, the limited research on the effectiveness of online learning in community colleges suggests this mode of instruction presents challenges to nontraditional students.

Effectiveness of Online Learning in a Community College Setting

Many of the studies measuring the effectiveness of online learning have been conducted with traditional students in four-year universities (Means et al., 2009, 2013). Students enrolled in a four-year university are more likely to attain a degree and come from homes with higher incomes and have parents who attended college than students in community college (NCES, 2002). Moreover, measuring the effectiveness of online learning with well-prepared, mostly white, traditional students in four-year universities is not generalizable to students enrolled in community colleges (Jaggars & Bailey, 2010).

Community colleges have expanded on and promoted online courses with the intent to provide more access, flexibility, and reduced costs to students. In 2008, 97% of two-year colleges offered online courses (Allen & Seaman, 2016). Barbules and Callister (2000) claimed that online courses are playing a growing role in reconfiguring postsecondary education due to demand, economics, and competition in the education market. Critics argued that the proliferation of online courses will serve to stratify higher education leading to more inequality and inferior educational offerings (Jaggars & Bailey, 2010; Noble, 2001). Despite the lack of strong empirical evidence that online learning is as effective or superior to face-to-face learning, online courses continue to expand at community colleges (Allen & Seaman, 2016).

Cox (2005) examined the institutional myths legitimizing the expansion of online courses in community colleges. Using extensive data from the Community College

Research Center at Teachers College, Cox (2005) conducted in-depth interviews at 15 community colleges in six states, and together, these states account for over one-third of the public community colleges in the United States. Over 600 administrators, faculty, and students were interviewed for the study. Cox (2005) contended that community college actors are “responding to a set of taken-for-granted ideas about online education” (p. 1756). The following are highlights from Cox’s (2005) findings: Administrators believed they must offer online courses to remain competitive and to increase student accessibility while faculty contested the viability of this mode of instructional delivery. Thus, the drive to increase online courses was influenced by organizational desires versus faculty-driven ideas around best practice. Moreover, community college administrators’ attempt to “fit in” as legitimate colleges drove them to adopt organizational structures of other high-status colleges - which includes promoting online learning, which may not be suitable for the nontraditional students they serve (Cox, 2005). Additionally, the myth that students must acquire technology-related skills required in the workplace has potentially justified the need for more online courses and perpetuates the myth of the need of providing technological literacy.

Research on community college student success in online courses is replete with cautionary tales of student failures (Jaggars et al., 2013). A comprehensive research overview of online course outcomes completed by the Community College Research Center at Columbia University found that, “Despite this rapid growth in online education, little is known about the effectiveness of online courses for community college students” (Jaggars et al., 2013, p. 1). Jaggars, Edgecombe, and Stacey (2013) conducted a longitudinal study from 2004-2008 and reported that online course failure/withdrawal rates were 32% in online courses versus 19% in face-to-face courses in 24 community colleges comprising over 185,000 students in the U.S. southern state system (Jaggars et al., 2013). In required mathematics courses the online failure/withdrawal rate was 25% versus 12% in face-to-face courses (Jaggars et al., 2013). Developmental mathematics courses had a failure/withdrawal rate of 62% in online courses versus 43% in face-to-face courses. Moreover, the research revealed that black males with lower prior GPAs had three times the failure/withdrawal rate than students with higher GPAs.

The aforementioned Means, Toyama, Murphy, Bakia, and Jones (2009) meta-analysis showed positive effects on student academic outcomes in online courses compared to face-to-face courses. Jaggars and Bailey (2010) analyzed those results and argued that the Means et al. (2009) findings do not hold for fully online, semester-length courses. Moreover, they contended the results are not generalizable to underprepared, nontraditional students typically found in community colleges (Jaggars & Bailey, 2010). Among the factors they deemed made the Means et al. (2009) study less generalizable included small sample sizes, traditional four-year university students, a bias towards non-typical college courses, and short duration courses. Jaggars and Bailey (2010) examined 28 studies (of 51 total) from the Means et al. (2009) study to compare results of online and face-to-face learning environments. They argued that the majority of the studies included in the Means et al. (2009) research were not relevant to the context of typical community college courses or typical community college students. They found that over half the studies concerned short (15 minute modules), topic-specific courses well-suited to the online learning context and not similar to semester-long, general education courses typically found in higher education courses (Jaggars & Bailey, 2010). Moreover, they pointed out selection bias in that the results were applicable only to higher-performing, motivated students. Additionally, no studies examined included low-income, underprepared students typically found in the community college setting.

Xu and Jaggars (2014) conducted extensive research on the performance gaps of students taking online and face-to-face courses in Washington State. Using a dataset containing 500,000 courses taken by over 40,000 community college students, the researchers examined the academic performance gaps in online learning performance among subgroups and academic subjects. They found that younger students, males, black students, and students with lower GPAs suffered the largest "decrements" in academic performance in online courses. Average persistence rates were 91.17% in online courses and noticeably lower than persistence rates of 94.45% in face-to-face courses. Average standardized grades were lower (-0.054) in online courses versus average standardized grades of 0.006 face-to-face courses. In terms of age, older students had lower persistence rates in face-to-face courses of 94% compared to 95% in face-to-face courses but surprisingly higher persistence rates in online courses of 91% compared to 90% persistence rates of younger students. Performance gaps were also found in academic subject areas between online and face-to-face courses. The results of this comprehensive study indicated that the typical community college student performed less well in online courses compared to face-to-face courses (Xu & Jaggars, 2014). It was suggested that screening, early warning, and scaffolding should be considered as potential interventions.

Mathematics Achievement and Remediation in Community Colleges

In 2012, over two million students were enrolled in two-year mathematics and statistics programs in two-year colleges. However, 57% of the students were enrolled in pre-college, noncredit courses (Olson & Labov, 2012). Moreover, research suggests that many of these students never reach college-level mathematics (Bailey et al., 2015 Olson & Labov, 2012; Xu & Dadgar, 2018). A known gap in mathematics instruction is the lack of understanding of how to integrate technologies to deliver instruction both in the classroom and online (Bragg, 2012).

The subject of remediation and developmental education in community colleges is of great interest to administrators and practitioners in community colleges. Over the past decade, community college personnel have reformed their traditional course offerings to accommodate students who need remedial support in all subjects, mathematics in particular (Bailey et al., 2015). However, proficiency in procedural algebra skills in remedial mathematics courses may not be adequate enough for preparing students for college-level mathematics (Quarles & Davis, 2017). Additionally, only 20% of students referred to developmental mathematics courses in community colleges continue on to pass the entry-level college course (Bailey et al., 2010; Xu & Dadgar, 2018). Online remedial mathematics courses hold the promise to address the need to provide a more flexible and effective way to deliver mathematics instruction to students in community colleges. However, the research on the effectiveness of teaching remedial mathematics online is inconclusive, and while some students can benefit from this instructional modality, many do not.

Ashby, Sadera, and McNary (2011) compared 167 students' academic outcomes in three different learning environments of an intermediate algebra course: fully online, blended, and face-to-face and found significant differences with student academic success. Their findings contradicted current research, which shows learning environments are equally effective. Completion rates for face-to-face students was 93%, blended students 70%, and online students 76%. In this study, online and blended students performed significantly lower on the Algebra Competency Examination than students in face-to-face classes when not taking attrition into account (Ashby, Sadera, & McNary, 2011). However, when taking attrition into account face-to-face students performed worse. With only three-quarters of the online students completing all assignments attrition clearly had an impact on student outcomes. Online students who did complete all assignments had the highest (85%) success rate in the course. While this study did not measure self-regulated learning, it can be posited that self-regulation and persistence likely had a large impact on student outcomes.

Zavarella (2008), in a similar study of community college students taking remedial mathematics courses, compared the success of 192 students registered in same course with different instructional delivery modes: face-to-face, blended, and online. Success was measured by withdrawal and completion rates. The study found withdrawal rates in computer-based courses to be double that of face-to-face courses. Data collected from students who withdrew indicated that they encountered challenges they did not expect. Additionally, the online students reported a lack of available tutorial services despite regular virtual office hours available from instructors. Help-seeking is a component of self-regulation skills that can be associated with academic success or retention.

Wladis, Conway, and Hachey (2015) investigated how ethnicity, gender, and other nontraditional student characteristics related to online learning outcomes in STEM courses in a community college setting. The study included 3,600 students from an urban community college in the Northeastern United States registered in online or face-to-face STEM classes. Learning outcomes were measured by completion of the course with a grade of C- (the minimum transfer credit) or higher. Results indicated that older males performed better online than in face-to-face courses. There was no interaction effect with regard to ethnicity in both online and face-to-face courses. Moreover, Wladis et al. (2015) pointed out that there may be factors other than the online learning environment associated with female failure rates in online STEM courses. Finally, mathematics/computer courses had larger gaps in course completion rates than science/computer courses, but the difference was not statistically significant. This research is useful to inform the hypothesis of the present study that age and gender are potential factors in determining online academic success.

Bahr (2008) investigated the long-term academic success of community college students who received remedial assistance in mathematics and achieved college-level mathematical skills. Academic success was defined as credential attainment or transfer to a four-year institution (Bahr, 2008). The study included over 85,000 community college students enrolled in 107 community colleges in California. Bahr (2008) concluded that remedial mathematics programs are highly effective at resolving skill deficiencies with community college students. Bahr (2008) found achievement outcomes of some students who completed remedial math courses comparable to the students who took college level mathematics. Unfortunately, Bahr (2008) also found that 75.4% of the students did not remediate successfully resulting in 81.5% of these students not completing a credential and not transferring to a four-year university. The study suggests that remediation can be very effective but only works for some students. Bahr (2008) further suggested that a strong predictor of mathematics success is a student's first mathematics grade (see also Wang, Wang, Wickersham, Sun, & Chan, 2017). Bahr (2008) posited that academic self-efficacy plays a role in academic performance and poor performance in a first math class would discourage further pursuit of mathematical competency.

Summary

As online learning continues to grow and expand in community colleges it is critical that educators understand the effectiveness of this instructional mode. The empirical evidence of the effectiveness of online learning is inconclusive. Moreover, there is a dearth of research with nontraditional students in community colleges. The proliferation of the acceptance of poorly defined terms, rapidly evolving technology, and a lack of rigorous validation has exacerbated the challenges of growing the theoretical and empirical research base of online learning.

Self-regulated learning skills potentially play an important role in student success in online learning contexts. The theoretical foundations of self-regulation are well-established. However, the empirical evidence of the role that self-regulation plays in student success is inconclusive and lacks a thorough understanding. While there is some evidence that self-regulation has a relationship to academic performance, simply teaching or supporting self-regulation in an educational setting may not be enough.

Success in mathematics in community colleges is essential for students to enter degree programs and earn credentials necessary for employment or credits to transfer to four-year universities. A significant number of students enter community college lacking the necessary preparation in mathematics required to begin taking college-level mathematics. Consequently, community colleges have had to reform traditional mathematics course offerings to accommodate students who need remedial support. Empirical evidence of student success in remedial mathematics, particularly in online settings, reveals poor academic success and low retention rates. Self-regulation skills potentially play a role in academic success in online mathematics courses in community college settings. However, more research is needed.

Chapter 3: Methodology

Introduction

The purpose of this study was to examine the relationship of students' self-regulated learning beliefs and academic risk factors to academic performance in three community college online mathematics courses. Final mathematics examination scores were the measure of students' academic performance. Students' self-regulated learning beliefs were measured using four subcomponents of the Motivated Strategies for Learning Questionnaire (MSLQ) (see Appendix B). Four academic risk factors – age, ethnicity, gender, and high school graduation status – were obtained from college records. The MSLQ questionnaire measures student beliefs related to the constructs of motivation and self-regulated learning skills. Results from the questionnaire responses were integrated with selected students' demographic records and final mathematics exam scores to analyze the relationship of self-regulated learning beliefs and academic risk factors to academic performance. Additionally, the moderating effects of self-regulation beliefs on academic risk factors were examined. This chapter describes the data collection methodology, participants in the study, procedures, sources of data, and ethical considerations.

Research Design and Rationale

Self-regulated learning, motivation, and skills can influence academic success in online learning courses (Cho & Heron, 2015). Additionally, certain demographic characteristics of students are considered risk factors associated with academic performance (Jost, Rude-Parkins, & Githens, 2012; Wang et al., 2013). The present study utilized statistical quantitative methods to examine the relationship of self-regulated learning beliefs and academic risk factors to academic performance. The study also investigated the strength of the moderating relationship of self-regulated learning beliefs on the relationship between academic risk factors and academic performance. The study utilized a subset of the MSLQ questionnaire to measure four subcomponents of motivation and learning skills: Task Value, Self-Efficacy for Learning and Performance, Metacognition Self-Regulation, and Effort Regulation. The statistical methods of correlation and multiple regression were used to evaluate the relationship of academic risk factors and self-regulated learning beliefs as independent variables to the dependent variable of academic performance. The interaction effect of self-regulated learning beliefs and academic risk factors was calculated to determine any moderating effects to academic performance.

Participants

Participants were enrolled in one of three online mathematics courses at an urban community college in Washington state in the fall quarter of 2017. The students represented a convenience sample comprised of three intact online mathematics classes: Algebra I, Algebra II, and College Algebra. The Algebra I and II courses were taught by one instructor and the College Algebra course was taught by a different instructor. It was projected that each course would have 30 students enrolled for a total population recruitment size of 90 students. It was estimated that 70% of the students would respond to the MSLQ self-regulated beliefs questionnaire for a total potential sample size of 63 respondents. The following demographic information was collected for each student who responded to the survey: gender, high school graduation status, ethnicity, and age.

The optimal sample size was calculated using the G*Power3 software version 3.1.9.3. The G*Power3 software calculates an optimal sample size using various inputs including effect size, number of variables, and desired level of significance (Faul et al., 2007). For the purposes of this study, the optimal sample size was calculated using a model comprising of two predictor variables, an effect size of .20, and a 0.95 confidence interval. The optimal sample size was computed as 81. In *a priory* power analysis, sample size *n* is computed as a function of the required power, the pre-specified significance level, and the population effect size to be detected with probability (Cohen, 1983. The power of a statistical test is the probability that the hypotheses will be rejected given that it is false. The null hypothesis is that self-regulation has no significant relationship to academic performance and does not moderate the relationship of academic risk factors to academic performance. Significance tests that have statistical power can more reliably discriminate between alternative hypotheses (Faul et al., 2007).

Instruments

The Motivated Strategies for Learning Questionnaire (MSLQ) was used for the present study. The MSLQ is a widely-used self-report instrument used to measure college student motivational beliefs and assess beliefs of specific self-regulation learning strategies (Duncan & McKeachie, 2005). The instrument was designed and developed in 1986 by a team of researchers from the National Center for Research to Improve Postsecondary Teaching and Learning (NCRIPTAL) and the School of Education at the University of Michigan (Duncan & McKeachie, 2005). Prior to the development of the MSLQ questionnaire, research on college student learning was often focused on learning styles or learning differences and criticized for the lack of theoretical and empirical evidence (Weinstein & Underwood, 1985).

Theoretical Framework

The development of the MSLQ questionnaire was based on the social-cognitive theory of motivation and the general cognitive model of learning and information processing theory (Pintrich et al., 1993). The social-cognitive theoretical framework model of motivation is comprised of three constructs: 1) expectancy, 2) value, and 3) effect (Pintrich et al., 1993). Expectancy refers to a student's belief in accomplishing a task, value focuses on why students engage in academic tasks, and the construct of effect is operational as a response to test anxiety (Pintrich et al., 1993). The cognitive model of learning and information processing theory is comprised of three constructs: 1) cognition, 2) metacognition, and 3) resource management (Weinstein & Mayer, 1986). Basic and complex cognitive strategies relate to processing information textually or orally, metacognition refers to one's ability to control and regulate one's own cognition, and resource management is related to one's control of other resources besides cognition (Pintrich et al., 1993). Using this theoretical framework, the MSLQ questionnaire includes 15 subscales, which measure each of the constructs of motivation and learning strategies (Pintrich et al., 1993).

Instrument Components

The MSLQ questionnaire measures college students' motivation and learning strategy skills using 15 subscales comprising 81 items scored on a 7-point Likert-like scale (1 = *not at all true of me* to 7 = *very true of me*). The questionnaire is designed to be modular and can be used in part or in its entirety (Duncan & McKeachie, 2005).

The motivation section comprises 31 items that assess one's goals and value beliefs, one's beliefs about one's skills to succeed, and one's anxiety about tests. Motivation is measured using six subscales: Intrinsic Goal Orientation, Extrinsic Goal Orientation, Task Value, Control of Learning Beliefs, Self-Efficacy for Learning and Performance, and Text Anxiety. The learning strategies section is comprised of 31 items that assess students' cognitive and metacognitive strategies and 19 items that assess students' management of different resources. Learning strategies are measured using nine subscales: Rehearsal, Elaboration, Organization, Critical Thinking, Metacognitive Self-Regulation, Time/Study Environmental Management, Effort Regulation, Peer Learning, and Help Seeking.

Use of Instrument for Present Study

For the purposes of this study the subscales of Task Value and Self-Efficacy for Learning and Performance were used to measure motivation, and the subscales of Metacognition Self-Regulation and Effort Regulation were used to measure self-regulated learning strategies. A total of 30 questions were included in the survey allocated as follows: Task Value (6), Self-Efficacy for Learning and Performance (8), Metacognitive Self-Regulation (12), and Effort Regulation (4). All questions were used verbatim from the MSLQ questionnaire (see Appendix B).

The four MSLQ subscales selected for the present study represented the subscales with the highest correlation to academic performance. All four subscales had moderate correlations to academic performance: Task Value (*r* = .22), Self-Efficacy for Learning and Performance (r = .41), Metacognitive Self-Regulation (r = .30), and Effort Regulation (r = .32) (Pintrich et al., 1993). Test Anxiety had a moderate correlation (r = -

.27) but was not selected for the study since it measures a distinct construct outside the scope of this study.

Instrument Validity and Reliability

The MSLQ questionnaire is a valid and reliable self-report instrument designed to assess motivation and use of learning strategies by college students (Duncan & McKeachie, 2005). The MSLQ questionnaire authors completed two confirmatory factor analyses to determine the utility of the model and the operationalization of each of the MSLQ subscales (Pintrich et al., 1993). A sample of college students (n = 356) consisting of thirty-seven classrooms, spanning fourteen subject domains, and five disciplines was used for the analyses (Pintrich et al., 1993).

The results of the confirmatory analyses for the motivational subscales indicated the lambda-ksi estimates ranging from .38 - .89 with an average value of .68. The test's authors note that "the Lambda-ksi estimates are analogues to factor loadings in an exploratory factor analysis and values of .8 or higher indicate well-defined latent constructs" (Pintrich et al., 1993, p. 807). Omnibus fit statistics constraining the 31 items to fall into the six subscales generated a x^2/df ratio of 3.49, a GFI of .77, and AGFI of .73, and an RMR of .07 indicating a best fit of the input data. The coefficient alphas of the motivational subscales are generally strong, indicating good internal consistency. Intrinsic goal orientation was strong at (.74) alpha, extrinsic goal orientation had more variability (.62) alpha, Task Value was very high (.90) alpha, control of learning beliefs had more variability (.68) alpha, Self-Efficacy for Learning and Performance had a very high (.93) alpha, and the text anxiety (.80) alpha indicated good internal consistency (Pintrich et al., 1993) (see Table 1).

The results of the confirmatory factor analysis for the learning strategies subscales of 50 items fell onto nine correlated latent factors and generated a x^2/df ratio of 2.26, a GFI of .78, and AGFI of .75, and an RMR of .08 indicating a best fit of the input data. The coefficient alphas of the learning strategies subscales were reasonable with most coefficient alphas above .70 (Pintrich et al., 1993). Rehearsal and Effort Regulation had coefficient alphas of (.69), organization strategies somewhat lower at (.64), and help-seeking low at (.52) alpha (Pintrich et al., 1993).

Based on the results from both confirmatory factor analyses it suggests the MSLQ has a relatively good reliability in terms of internal consistency (Gall et al., 2015; Pintrich et al., 1993). The instrument appears to be a valid framework for assessing student motivation and learning strategies of college students.

Instrument Predictive Validity Analysis

A primary reason for selecting the MSLQ questionnaire instrument for the present study was its reasonable predictive validity to academic performance. To determine predictive validity, the MSLQ subscales were correlated by its developers with students' final course grades. A majority of the subscales were significantly and positively correlated and in the expected direction to final grades demonstrating predictive validity (Pintrich et al., 1993). Peer learning was the only subscale not positively correlated to final grades.

Pintrich et al. (1993) found correlations with final course grades for motivation scales as follows: intrinsic goal orientation moderate correlation (r = .25), extrinsic goal orientation weak correlation (r = .02), Task Value moderate correlation (r = .22), control of learning beliefs weak correlation (r = .13), Self-Efficacy for Learning and Performance strong correlation (r = .41), and text anxiety negatively moderate correlation (r = -.27). Correlations with final course grades for the learning strategy scales were as follows: rehearsal weak correlation (r = .05), elaboration moderate correlation (r = .22), organization weak correlation (r = .17), critical thinking weak correlation (r = .15), Metacognitive Self-Regulation moderate correlation (r = .30), time/study environmental management moderate correlation (r = .28), Effort Regulation moderate correlation (r = .32), peer learning weak correlation (r = -.06), and help seeking weak correlation (r = .02) (see Table 1).

Table 1

Internal Reliability Coefficients and Correlations with Final Course Grades for Motivation and Learning Strategies Scales

Scale	Coefficient Alpha	Correlation with Final Course Grade
Motivation Scales		
Intrinsic Goal Orientation	.74	.25
Extrinsic Goal Orientation	.62	.02
Task Value	.90	.22
Control of Learning Beliefs	.68	.13
Self-Efficacy for Learning and Performance	.93	.41
Test Anxiety	.80	-.27
Learning Strategies Scales		
Rehearsal	.69	.05
Elaboration	.75	.22
Organization	.64	.17
Critical Thinking	.80	.15
Metacognitive Self-Regulation	.79	.30
Time & Study Environment Management	.76	.28
Effort Regulation	.69	.32
Peer Learning	.76	-.06
Help-Seeking	.52	.02

The predictive validity of the scales shows the correlations to academic performance and in the expected direction, adding to the validity of the scales (Pintrich et al., 1993). The results of this study suggested that the MSLQ questionnaire had relatively good internal consistency and was an appropriate instrument for the present study.

Procedures and Data Sources

Students enrolled in one of three online mathematics courses at an urban community college were asked to voluntarily complete the MSLQ questionnaire. A modest amount of course credit, defined by the instructors, was offered as an incentive to participate in the study. The questionnaire consisted of thirty questions regarding self-reported beliefs about motivation and learning strategies related to the particular course. The email invitation to participate in the study was posted on the course website and included a statement indicating that all responses were anonymous and confidential (see Appendix C). A link to the questionnaire was provided on the course website.

The survey was created and hosted by a secure, commercial survey company called surveymonkey.com. The survey was available to students during weeks two through four of the academic quarter. Results of the questionnaire were initially exported from surveymonkey.com and imported into Microsoft Excel spreadsheet program. Each set of questions related to a specific subscale was summarized as a single score for each respondent.

The Microsoft Excel spreadsheet was encrypted and sent to the Executive Director of Institutional Effectiveness at the community college. Confidential student identification numbers were removed and the following demographic data for each respondent was added to the spreadsheet: gender, ethnicity, high school graduation status, and age. The spreadsheet was returned to the researcher and uploaded into IBM SPSS version 25 for analysis. At the end of the quarter, final mathematics examination scores were added to the original spreadsheet and sent to the researcher. The final examination scores were added to the IBM SPSS dataset for final analysis.

Ethical Considerations

An Internal Review Board (IRB) at Seattle Pacific University (SPU) reviewed the research procedures and the study was approved on September 5, 2017**,** under exempt review as meeting the requirement of “no more than minimal risk” as stated in the *SPU IRB User Guide* (Seattle Pacific University, 2012, p. 5). The community college in this study completed an IRB and approved the study on October 11, 2017 (see Appendix D).

It was assumed there was a minimal risk to the students participating in the study answering questions related to their motivational and learning strategies beliefs. Students were explicitly assured their responses were anonymous and confidential providing further confidence that the students faced minimal academic or personal risk by participating in the study.

Data Analysis

Descriptive and Inferential Statistics

Descriptive statistics including mean, median, mode, and standard deviation were calculated for all demographic data and for each subscale and individual questions measured in the MSLQ questionnaire. Final exam scores were converted to z-scores for each class to reduce any bias or variability in grading scales used by the instructors. Bivariate Pearson correlation coefficients were calculated to investigate the linearity between the indicator variables and their latent variables. Inferential analysis, using multiple regression, was conducted to determine relative contributions of predictor variables to the dependent variable of academic performance.

Comparison of Self-Regulated Learning Subscales and Academic Risk Factors

Reliability analysis was conducted on all self-regulation subscales to determine internal consistency reliabilities using the Cronbach Alpha scale (Vogt & Johnson, 2016). Simple Pearson correlations were conducted to determine relationships between all independent variables and to the dependent variable of academic performance. A test of statistical significance was performed with a probability significance level of .95 confidence (Gall et al., 2015). Only independent variables that were statistically significant were selected for further analysis.

Inferential Analysis of Self-Regulated Learning Variables and Academic Risk Factors

Correlational analyses were conducted to evaluate the relationship of academic risk factors and self-regulated learning factors to academic performance. Hierarchical regression analysis was conducted to measure the relative contribution of each self-regulated learning subscale and academic risk factors to academic performance. Beta values were analyzed to determine each interdependent variable contribution.

Analysis of Academic Risk Factors as Moderators to Predicting Academic Performance

The interaction effect of the subscales Self-Efficacy for Learning and Performance and Task Value was calculated for each risk factor predictor variable. The interaction effect was measured to determine the magnitude or sense of the relationship between these variables to academic performance. The level of significance used for the analyses was set at $\alpha = .05$.

Chapter 4: Results

Introduction

This chapter summarizes the results of the present study and analyzes the extent of the relationship of self-regulated learning and academic risk factors to academic performance using inferential statistics. Descriptive statistics were computed for each independent variable, the criterion variable, and for each question response on the MSLQ questionnaire to confirm normal distribution of the data. Reliability analysis of each MSLQ subscale set of questions was computed using Cronbach's alpha.

Inferential statistical analysis was conducted using multi-step hierarchical multiple regression with IBM SPSS version 25 statistical program. The level of significance for this analysis was < .05 (Gall et al., 2015). Moderating effects of the independent variables were computed using hierarchical multiple regression analysis.

The purpose of this study was to examine the relationship of self-regulated learning and academic risk factors to academic performance in three community college online mathematics courses. The study was designed to answer the following research questions:

1. What is the relationship of self-reported, self-regulated learning beliefs to academic performance, as measured by final exam score, in an online learning environment?
2. What is the relationship of selected academic risk factors to academic performance, as measured by final exam score, in an online learning environment?
3. To what extent do self-regulated learning beliefs moderate the relationship of academic risk factors to academic performance?

Sample Size Analysis

Participants were recruited from a community college located in a large metropolitan city. A total of 82 students from three intact online mathematics courses received an offer to participate in the study. Participation required responding to 30 items on the MSLQ questionnaire. A total of 52 students responded to the survey representing a 63% response rate. A response rate greater than 60% can be considered adequate to minimize the effect of nonresponse rate bias (Fincham, 2008; Fink, 1995).

An analysis of optimal sample size of the study was calculated prior to identifying the target courses for inclusion in the study. The optimal sample size for the study was calculated using the G*Power3 software. The present study originally considered four online mathematics courses but one course was dropped from the schedule, thus, reducing the potential size of the sample.

The optimal *n* size was calculated using the following parameters: an effect size estimate of .20, a desired significance level of $p < .05$, and two predictor variables in the model. The optimal sample size was calculated at 81 participants (Faul et al., 2007). Based on the above calculation of an optimal sample *n* size, the final number of 52 student participants in the present study was less than optimal and is noted in the research limitations section of this study. Due to missing student identification information, three responses were eliminated from the dataset resulting in 49 valid responses.

Descriptive Statistics of Course Enrollment and Participant Demographics

Each mathematics course was taught fully online with no face-to-face component. Table 2 shows a majority (59.2%) of the students in the sample were enrolled in Algebra I or II taught by the same instructor. A total of 20 students in the sample were enrolled in College Algebra, taught by a different instructor.

Table 2

Frequency of Participant Enrollment in Online Mathematics Courses

Course	Frequency	Valid Percent
Mathematics 094 (Algebra I)	18	36.7
Mathematics 095 (Algebra II)	11	22.5
Mathematics 102 (College Algebra)	20	40.8

Table 3 represents the gender distribution of the sample. Females represented a majority (61.2%) of the participants in the study accounting for a much higher percentage than the overall representation (49%) of females in the college's current enrollment.

Table 3

Frequency of Participant Gender

Gender	Frequency	Valid Percent
Female	30	61.2
Male	19	38.8

Figure 1 represents the age and frequency distribution of the convenience sample in the study. Student ages ranged from 17 to 54 years. The average participant age was 27.94 (SD = 8.29) years, which is consistent with the median age (28 years) of students in this college's current enrollment. The largest concentration of participants is between the ages of 20-30 years old representing 57.1% of the convenience sample. The age distribution is within normal limits. Descriptive statistics can be found in Table 4.

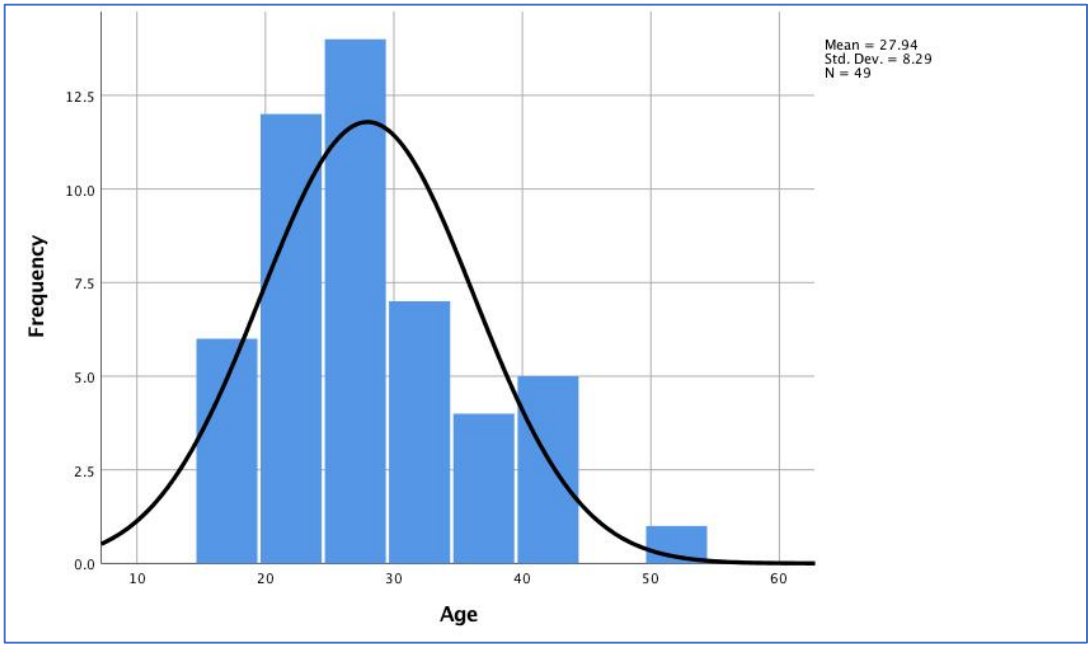

Figure 1. Age frequency and distribution of participants.

Table 4

Participant Age Descriptive Statistics

	Minimum	Maximum	M	Skewness	Kurtosis
Age	17	54	27.94	.951	.688

Table 5 represents the ethnic breakdown of the convenience sample. A majority (53.1%) of the students in the convenience sample were students of color representing a slightly higher percentage of students of color (45%) than found in the general population of the college.

Table 5

Ethnic Backgrounds of Participants

Ethnicity	Frequency	Valid Percent
African American	4	8.2
Asian/Pacific Islander	7	14.3
International	3	6.1
Latino/Hispanic	10	20.4
No Response	5	10.2
Other Race	2	4.1
White	18	36.7

Table 6 represents the high school graduation status of the participants. A majority (85.7%) of the students indicated they had graduated from high school. Data were also collected on the amount of post-high school education of the participants. Of the respondents, 20 students (40.8%) indicated they had taken some post-high school higher education courses. Some students enrolled in the College Algebra course indicated that they had earned an associate's or bachelor's degree. This independent variable lacks sufficient frequency distribution to provide a meaningful contribution to the analysis and thus was not included in the regression analysis.

Table 6

High School Graduation Status

High School Graduate	Frequency	Valid Percent
Yes	42	85.7
No	3	6.1
No Response	4	8.2

Descriptive Statistics of Final Examination Mathematics Scores

Mathematics final examination scores were obtained at the end of the quarter from each instructor. Mathematics final examination scores represent academic performance on mathematics assessments aligned to curriculum content. The scores do not necessarily represent the final grade in the course. Two students withdrew from their respective courses. One student who withdrew did have a mathematics score and it was included in the dataset. Eight students received a score of zero on their final mathematics exam due to not taking the final examination. Exploratory analysis was conducted removing the participants who had a zero score to determine any significant effect on the results. Standardized z-scores were computed for all mathematics final examination scores to account for the potential variability of instructor scoring in the three intact courses (Gall et al., 2015). The data suggest a normal distribution. However, Algebra I scores did exhibit a negative skewness indicating a concentration towards lower scores. College Algebra exhibited slight kurtosis but within normal distribution levels. Descriptive statistics for mathematics final exam scores can be found in Table 7.

Table 7

Descriptive Statistics for All Mathematics Final Exam Scores in each Online Mathematics Course

	n	Min	Max	*M*	*SD*	Skewness	Kurtosis
Algebra I	18	10	102	80.94	24.05	-1.778	1.038
Algebra II	11	0	99	62.73	36.07	-.886	-.856
College Algebra	19	0	96	56.32	40.79	-0.639	-.1.512

Descriptive Statistics of Self-Regulated Learning MSLQ Questionnaire Subscale Responses

Average response scores were calculated for the sum of all scores for each set of questions associated with each subscale on the questionnaire. The average scores ranged from 4.87 to 5.53. Average scores of 3 and below are considered weak and scores in the range of 4 to 7 are considered moderate or strong levels of self-regulated beliefs (Pintrich et al., 1993). The average scores indicate participants in the study exhibited an overall moderate to high level of self-regulated learning beliefs in all four subscales.

All subscales were analyzed to determine normality of the distribution of all responses. All four subscales' descriptive statistics exhibited a normal skewness range (-.004 to -.804) and normal kurtosis range (.051 to -.765) indicating normal distribution of data (Gall et al., 2015) (see Table 8).

Table 8

Descriptive Statistics for MSLQ Questionnaire Subscales

Item	No. of Items	Min	Max	*M*	*SD*	Ave Score	Skewness	Kurtosis
Task Value	6	13	42	33.22	7.16	5.53	-.804	.171
Self-Efficacy for Learning and Performance	8	14	56	38.96	11.25	4.87	-.341	-.765
Metacognitive Self-Regulation	12	33	82	58.61	10.77	4.88	-.004	-.311
Effort Regulation	4	9	28	22.02	4.45	5.50	-.597	.051

Internal Reliability Analysis of Self-Regulated Learning MSLQ Questionnaire Responses

Internal reliability tests were conducted to confirm construct consistency of the item responses to the MSLQ questionnaire. Cronbach's alpha scores in the present study indicated strong internal consistency. The scores were consistent with previous research by Pintrich et al.'s (1993) reporting of Cronbach's alpha for each subscale: Task Value (.90), Self-Efficacy for Learning and Performance (.93), Metacognitive Self-Regulation (.79), and Effort Regulation (.69) (see Table 9).

Table 9

Cronbach's Alpha Internal Reliability Measures for each MSLQ Subscale

Subscale	No. of Items	Cronbach's Alpha
Task Value	6	0.87
Self-Efficacy for Learning and Performance	8	0.95
Metacognitive Self-Regulation	12	0.75
Effort Regulation	4	0.74

MSLQ Questionnaire Subscale Correlations

Subscale items were analyzed revealing moderate and significant correlations between items. Positive correlations were expected between subscales measuring motivation (Task Value and Self-Efficacy for Learning and Performance) and subscales measuring learning skills (Metacognitive Self-Regulation and Effort Regulation). However, subscales Self-Efficacy for Learning and Performance and Metacognitive Self-Regulation, while measuring different attributes of self-regulated learning, had a higher than expected statistically significant correlation (.570) (see Table 10).

Table 10

MSLQ Questionnaire Subscale Pearson's Correlations Matrix

	Task Value	Self-Efficacy for Learning and Performance	Metacognitive Self-Regulation	Effort Regulation
Task Value	1	$.543^{**}$	$.461^{**}$	$.402^{**}$
Self-Efficacy for Learning and Performance	$.543^{**}$	1	$.570^{**}$	$.307^{*}$
Metacognitive Self-Regulation	$.461^{**}$	$.570^{**}$	1	$.592^{**}$
Effort Regulation	$.402^{**}$	$.307^{*}$	$.592^{**}$	1

$^{*}p < .05$. $^{**}p < .01$.

Descriptive Statistics for Self-Regulated Learning Subscale Responses

Each participant answered 30 items on the MSLQ questionnaire. The responses indicate self-reported measures ranking each question on a 7-point Likert-like scale (1 = *not at all true of me* to 7 = *very true of me*). Descriptive statistics were analyzed for each question response to determine the measure of self-regulation strength and dispersion of scores (see Appendix A). Following is a summary of the descriptive statistics for all questions on each subscale.

Task Value Subscale

Descriptive statistics for the Task Value subscale individual questions indicate a moderate to strong strength of Task Value (M = 4.65 – 6.49). The question related to the importance of learning the course material indicated the highest mean score (M = 6.49). Scores of 3 and below are considered weak and scores in the range of 4 to 7 are considered moderate or strong (Pintrich et al., 1993).

All questions were analyzed to determine normality of the distribution of responses with four questions exhibiting a normal skewness range (-.461 to -.913) and normal kurtosis range (-.087 to -.833) (Gall et al., 2015). However, the question related to the measuring of the importance of learning course material exhibited high negative skewness (-2.175) and high positive kurtosis (4.793). The question related to the importance of understanding course material exhibited a slightly high negative skewness (-1.134) (see Appendix A).

Internal consistency and reliability of the responses to the subscale for Task Value questions in the present study was strong ($\alpha = 0.87$). Pintrich et al. (1993) determined reliability estimates for the Task Value subscale of the MSLQ questionnaire to be $\alpha = 0.90$. The results of the present study indicate strong alignment to internal reliability found by Pintrich et al. (1993).

Self-Efficacy for Learning and Performance Subscale

Descriptive statistics for the Self-Efficacy for Learning and Performance subscale individual questions indicate a moderate strength of Self-Efficacy for Learning and Performance (M = 4.31 – 5.73). Scores of 3 and below are considered weak and scores in the range of 4 to 7 are considered moderate or strong (Pintrich et al., 1993). The question related to confidence of learning basic concepts in the course indicated the highest mean score (M = 5.73).

All questions were analyzed to determine normality of the distribution of responses with all questions exhibiting a negative skewness range (-.113 to -.794) and a negative kurtosis range (-.329 to -1.055). The ranges are all within normal limits (Gall et al., 2015) (see Appendix A).

Internal consistency and reliability of the responses to the subscale for Self-Efficacy for Learning and Performance questions in the present study were strong (α =

0.95). Pintrich et al. (1993) determined reliability estimates for Self-Efficacy for Learning and Performance subscale of the MLSQ questionnaire to be $\alpha = 0.93$. The results of the present study indicate strong alignment to internal reliability found by Pintrich et al. (1993).

Metacognitive Self-Regulation Subscale

Descriptive statistics for the Metacognitive Self-Regulation subscale individual questions indicate a moderate strength of metacognitive self-regulation (M = 3.33 – 6.22). Scores of 3 and below are considered weak and scores in the range of 4 to 7 are considered moderate or strong (Pintrich et al., 1993). The question related to the strategy to resolve confusion indicated the highest mean score (M = 6.22).

All questions were analyzed to determine normality of the distribution of responses with the majority of questions exhibiting a negative skewness range (-.329 to -1.055) and a positive kurtosis range (-.023 to 2.244). The question related to understanding concepts exhibited high kurtosis (2.244) and high skewness (-1.218). A majority of the questions exhibited ranges within normal limits (Gall et al., 2015) (see Appendix A).

Internal consistency and reliability of the responses to the subscale for Metacognitive Self-Regulation questions in the present study were strong (α = 0.75). Pintrich et al. (1993) determined reliability estimates for Metacognitive Self-Regulation subscale of the MLSQ questionnaire to be $\alpha = 0.79$. The results of the present study indicate strong alignment to internal reliability found by Pintrich et al. (1993).

Effort Regulation Subscale

Descriptive statistics for the Effort Regulation subscale individual questions indicate a moderate strength of Effort Regulation (*M* = 5.37 – 5.63). Scores of 3 and below are considered weak and scores in the range of 4 to 7 are considered moderate or strong (Pintrich et al., 1993).

All questions were analyzed to determine normality of the distribution of responses with the majority of questions exhibiting a negative skewness range (-.364 to -1.097) and a kurtosis range (-.890 to 1.051). The questions exhibited ranges within normal limits (Gall et al., 2015) (see Appendix A).

Internal consistency and reliability of the responses to the subscale for Effort Regulation questions in the present study were strong (α = 0.74). Pintrich et al. (1993) determined reliability estimates for Effort Regulation subscale of the MLSQ questionnaire to be α = 0.69. The results of the present study indicate strong alignment to internal reliability found by Pintrich et al. (1993).

Inferential Analysis using Correlation and Multiple Regression

Correlational analyses were conducted to evaluate the relationship of academic risk factors and self-regulated learning factors to academic performance. Prior to the analyses, all independent variables were evaluated for normality. The criterion variable of academic scores was computed as z-scores to account for the potential variability of instructor scoring in three different courses. Moderating influences of self-regulation factors to academic risk factors were analyzed using multiple regression.

Research Question 1: What is the relationship of self-reported, self-regulated learning beliefs to academic performance, as measured by final exam score, in an online learning environment?

The total score for each group of items on each subscale of the MSLQ questionnaire was computed for each participant. The score was correlated to final exam mathematics scores using a z-score calculation as the criterion variable. Each self-regulation variable was analyzed for correlation to academic performance. The variable Task Value had a statistically significant correlation to academic performance (.330, p = .011). The variable Self-Efficacy for Learning and Performance also had a significant correlation (.430, p = .001). Metacognitive Self-Regulation and Effort Regulation did not show significant correlations to academic performance (see Table 11).

Some of the results were similar to prior research by Pintrich et al. (1991), which found the following correlations to academic performance: Task Value (.22), Self-Efficacy for Learning and Performance (.41), Metacognitive Self-Regulation (.30), and Effort Regulation (.32). The subscales Self-Efficacy for Learning and Performance and Task Value did have statistically significant positive correlations to academic performance greater than Pintrich et al.'s (1993) prior research findings.

Table 11

Correlation of Predictors of Self-Regulation to Academic Performance

Self-Regulation Variable	Correlation to Academic Performance	Sig.
Task Value	.330	.011*
Self-Efficacy for Learning and Performance	.430	.001**
Metacognitive Self-Regulation	.198	.089
Effort Regulation	.130	.189

*p < .05. **p < .01.

Exploratory analysis was conducted to account for eight students who had an academic score of zero. Removing these from the dataset resulted in an increased statistically significant positive correlation to academic performance for Task Value (.385, p = .006) and a slightly less statistically significant positive correlation for Self-Efficacy for Learning and Performance (.397, p = .005). Metacognitive Self-Regulation had an increased correlation to academic performance (.257, p = .053) and Effort Regulation had a slightly increased correlation to academic performance (.149, p = .177) (see Table 12). The hypothesis that students with high self-regulated learning beliefs will achieve significantly higher academic performance, as measured by final exam score, than students with lower self-regulated learning beliefs was supported for the subscales of Self-Efficacy for Learning and Performance and Task Value.

Table 12

Correlation of Predictors of Self-Regulation to Academic Performance with Eight Zero Scores Removed

Self-Regulation Variable	Correlation to Academic Performance	Sig.
Task Value	.385	.006**
Self-Efficacy for Learning and Performance	.397	.005**
Metacognitive Self-Regulation	.257	.053
Effort Regulation	.149	.177

*p < .05. **p < .01.

Research Question 2: What is the relationship of selected academic risk factors to academic performance, as measured by final exam score, in an online learning environment?

Three academic risk independent variables were correlated to final mathematics scores using a z-score calculation. Each academic risk variable was analyzed for correlation to academic performance. None of the variables had any significant correlations (see Table 13). No significant predictive relationship was found between academic risk factors to academic performance as measured by final mathematics examination scores. The hypothesis that students with personal characteristics associated with academic risk will achieve significantly lower academic performance, as measured by final examination score, than students with personal characteristics not associated with academic risk was not supported.

Table 13

Academic Risk Factors Correlation to Academic Performance

Academic Risk Factor	Correlation to Academic Performance	Sig
Age	-.131	.188
Gender	.119	.210
Ethnicity	-.033	.412

* $p < .05$ ** $p < .01$

A multiple regression analysis was conducted to analyze all independent variables as predictors of academic performance. Table 14 shows the results of the regression analysis. Model 1 indicated a statistically significant positive correlation only with Self-Efficacy for Learning and Performance to academic performance (.404, p = .030). Regression analysis in Model 2 showed no statistically significant relationships of independent variables to academic performance.

Table 14

Linear Model Coefficients of Predictors of Academic Performance

Model		B	SE B	β	Sig.
1	Constant	-1.521	.826		.073
	Self-Efficacy for Learning and Performance	.035	.016	.404	.030*
	Effort Regulation	-.001	.038	-.004	.980
	Metacognitive Self-Regulation	-.010	.018	-.107	.588
	Task Value	.021	.023	.159	.356
2	Constant	-1.884	1.078		.088
	Self-Efficacy for Learning and Performance	.033	.017	.383	.060
	Effort Regulation	-.022	.040	-.011	.951
	Metacognitive Self-Regulation	-.008	.018	-.093	.648
	Task Value	.024	.024	.177	.328
	Ethnic Background	.122	.288	.061	.673
	Gender	.270	.281	.136	.342
	Age	-.009	-.072	-.072	.643

* $p < .05$ ** $p < .01$

Research Question 3: To what extent do self-reported, self-regulated learning beliefs moderate the relationship of academic risk factors to academic performance?

Hierarchical multiple regression analysis was conducted to test the predicted moderating effects of self-regulation on academic risk factors. The variable Self-Efficacy for Learning and Performance and Task Value were the only subscales that indicated any significant correlations to academic performance and thus warranted further analysis.

A summary of the interaction effects for all independent variables can be found in Table 15. Beta values for the moderating relationship of Self-Efficacy for Learning and Performance on gender, age, and ethnicity suggest a possible relationship. However, likely due to the small *n* of the convenience sample the results are not statistically significant. The beta values for the moderating relationship of Task Value on gender, age, and ethnicity suggest a possible relationship. However, given the small *n* of the convenience sample the results are not statistically significant. The interaction effect of Task Value and age suggests multicollinearity with the independent variables of Task Value and age.

Table 15

Multiple Regression Analysis Summary: Moderating Effects of Self-Efficacy for Learning and Performance and Task Value on Academic Risk Factors to Academic Performance

Self-Regulation Subscale	B	SE B	ß	t	Sig.
Self-Efficacy for Learning and Performance					
AgexSELP	-.001	.002	-.272	-.432	.668
GenderxSELP	-.014	.024	-.361	-.596	.554
EthnicityxSELP	-.016	.024	-.321	-.680	.500
Task Value					
AgexTaskValue	.005	.003	1.831	1.616	.113
GenderxTaskValue	-.020	.039	-.407	-.507	.615
EthnicityxTaskValue	.022	.038	.382	.578	.567

Linear Model Coefficients Interaction Effect of Academic Risk Factors and Self-Efficacy for Learning and Performance

The moderating effect of the independent variable Self-Efficacy for Learning and Performance was evaluated for all three academic risk factors. While beta values suggest a possible interaction effect, none were significant (see Tables 16, 17, and 18).

Table 16

Linear Model Coefficients Interaction Effect Age and Self-Efficacy for Learning Performance

Model		B	SE B	ß	t	Sig.
1	Constant	.433	.504		.859	.395
	Age	-.016	.017	-.131	-.895	.375
2	Constant	-1.273	.724		-1.758	.086
	Age	-.005	.016	-.042	-.304	.763
	SELP	.036	.012	.421	3.065	.004
3	Constant	-1.962	1.754		-1.119	.269
	Age	.018	.057	.154	.325	.747
	SELP	.056	.047	.647	1.197	.238
	AgexSELP	-.001	.002	-.272	-.432	.668

Table 17

Linear Model Coefficients Interaction Effect Gender and Self-Efficacy for Learning and Performance

Model		B	SE B	ß	t	Sig.
1	Constant	-.379	.486		-.780	.440
	Gender	.236	.290	.119	.815	.419
2	Constant	-1.1885	.638		-2.953	.005
	Gender	.267	.264	.135	1.012	.317
	SELP	.037	.011	.435	3.268	.002
3	Constant	-2.655	1.442		-1.841	.072
	Gender	.812	.953	.410	.853	.398
	SELP	.057	.035	.664	1.633	.110
	Gender xSELP	-.014	.024	-.361	-.596	.554

Table 18

Linear Model Coefficients Interaction Effect Ethnicity and Self-Efficacy for Learning and Performance

Model		B	SE B	ß	t	Sig.
1	Constant	.025	.180		.136	.892
	Ethnicity	-.066	.295	-.033	-.222	.825
2	Constant	-1.489	.500		-2.975	.005
	Ethnicity	.074	.272	.037	.271	.787
	SELP	.038	.012	.436	3.203	.003
3	Constant	-1.765	.647		-2.728	.009
	Ethnicity	.693	.951	.347	.729	.470
	SELP	.044	.016	.516	2.861	.006
	EthnicityxSELP	-.016	.024	-.321	-.680	.500

Linear Model Coefficients Interaction Effect of Academic Risk Factors and Task Value

The moderating effect of the independent variable Task Value was evaluated for all three academic risk factors. While beta values suggest a possible interaction effect, none were significant (see Tables 19, 20, and 21).

Table 19

Linear Model Coefficients Interaction Effect Age and Task Value

Model		B	SE B	ß	t	Sig.
1	Constant	.433	.504		.859	.395
	Age	-.016	.017	-.131	-.895	.375
2	Constant	-.998	.738		-1.353	.183
	Age	-.021	.017	-.179	-1.284	.206
	Task Value	.048	.019	.355	2.542	.015
3	Constant	3.575	2.921		1.224	.228
	Age	-.187	.103	-1.561	-1.803	.078
	Task Value	-.088	.086	-.653	-1.023	.312
	AgexTask Value	.005	.003	1.831	1.616	.113

Table 20

Linear Model Coefficients Interaction Effect Gender and Task Value

Model		B	SE B	ß	t	Sig.
1	Constant	-.379	.486		-.780	.440
	Gender	.236	.290	.119	.815	.419
2	Constant	-1.914	.790		-2.423	.019
	Gender	.258	.276	.130	.933	.356
	Task Value	.045	.019	.334	2.398	.021
3	Constant	-2.975	2.240		-1.328	.191
	Gender	.915	1.327	.462	.690	.494
	Task Value	.077	.066	.570	1.174	.247
	GenderxTask Value	-.020	.039	-.407	-.507	.615

Table 21

Linear Model Coefficients Interaction Effect Ethnicity and Task Value

Model		B	SE B	ß	t	Sig.
1	Constant	.025	.180		.136	.892
	Ethnicity	-.066	.295	-.033	-.222	.825
2	Constant	-1.463	.659		-2.221	.031
	Ethnicity	-.040	.282	-.020	-.143	.887
	Task Value	.045	.019	.329	2.340	.024
3	Constant	-1.091	.924		-1.181	.244
	Ethnicity	-.774	1.302	-.387	-.595	.555
	Task Value	.033	.027	.247	1.229	.226
	EthnicityxTask Value	.022	.038	.382	.578	.567

In conclusion, the hierarchical multiple regression analysis in the present study did not support the hypothesis that self-regulated learning beliefs significantly moderate the relationship of academic risk factors to academic performance. However, Self-Efficacy for Learning and Performance and Task Value did significantly correlate to academic performance.

Summary of Results

Descriptive statistics suggested that the data collected in the MSLQ survey and demographic data obtained from the college exhibited relatively normal distributions. The response rate (63%) to the survey was strong providing a good representation from each online mathematics class included in the study. Reliability of the responses to the survey questions was analyzed and found to be consistent with the expected outcomes (Pintrich et al., 1993).

Academic risk factors, defined as gender, ethnicity, and age, showed no statistically significant relationship to academic performance. No moderating effects of Task Value and Self-Efficacy for Learning and Performance to academic risk factors were found. However, Task Value and Self-Efficacy for Learning and Performance were found to have positive and significant correlations to academic performance.

Chapter 5: Discussion

Introduction

The purpose of this study was to examine the relationship of self-regulated learning beliefs and academic risk factors to academic performance in three community college online mathematics courses. Additionally, this study analyzed the moderating effects of self-regulation on academic risk factors. The responses to the MSLQ questionnaire subscales of Task Value and Self-Efficacy for Learning and Performance do suggest a possible relationship to academic performance. The results also indicate that academic risk factors did not predict academic performance in the present study. Self-regulation independent variables did not affect the strength of the relationship between academic risk factors and academic performance. The hypothesis that students with higher levels of self-regulation would achieve higher academic success than those with lower levels of self-regulation was not supported for all subscales measured.

This chapter provides the results of the analysis in relation to the research questions and to the hypotheses of the study. It also addresses the implications of the findings, the limitations of the study, areas of suggested future research, and modest recommendations for practitioners.

Self-Regulation and Academic Performance

The MSLQ questionnaire results indicate that participants in the study exhibited an overall moderate level of self-regulated learning beliefs in all four subscales. The mean score for each subscale in the present study was consistent with the internal consistency and reliability results reported by Pintrich et al. (1993) and similar to the mean scores reported by Cho and Heron (2015). In the present study, only Task Value and Self-Efficacy for Learning and Performance yielded statistically significant positive correlations to academic performance. Surprisingly, Metacognitive Self-Regulation and Effort Regulation did not significantly correlate to academic performance, a finding contrary to Pintrich et al.'s (1993) study, which reported predictive validity with all four subscales used in the present study. One possible explanation for this difference may be that metacognition was not a requirement or an encouraged practice in the mathematics courses and thus was probably not practiced by students. Additionally, the study's small sample size (n = 49) was arguably a factor as the relationship strength of Effort Regulation to academic performance was not detectable.

Perhaps the most interesting finding was the incongruous result regarding the relationship between Self-Efficacy for Learning and Performance beliefs and academic performance. While Self-Efficacy for Learning and Performance beliefs correlated to academic performance (.430, p = .001), eight students (16.3%) in the study self-reported Self-Efficacy for Learning and Performance beliefs that did not correspond to their academic performance. Results showed that three students reported a Self-Efficacy for Learning and Performance belief score greater than 45, which was higher than the mean score (M = 38.96). All three of these students had final examination scores below 75, likely resulting in a failing grade in their course. Results also showed that five students reported a Self-Efficacy for Learning and Performance belief score of less than 30, lower than the mean score (M = 38.96). All of these students had an academic score higher than the mean score, with three students receiving a likely passing score for their course. These results suggest that student self-reports of their Self-Efficacy for Learning and Performance beliefs were not necessarily a reliable indicator of academic performance in the present study. The academic risk factors of ethnicity, gender, age, and high school graduation status had no obvious patterns of correlation to Self-Efficacy for Learning and Performance beliefs to explain this inconsistency. This result illustrates a possible inherent weakness of the questionnaire because of the potential for validity bias related to socially desirable responses to a questionnaire that relies on self-reported beliefs (Duncan & McKeachie, 2005; Fowler, 2014). However, Duncan and McKeachie (2005) reported that while actual observations or behavior indicators provide better validity than self-reports, the measures of response bias of the MSLQ questionnaire did not appear to account for any significant variance or change the results of the studies they evaluated.

Another concerning finding was that 17 students received a final examination score that indicated they would likely fail the course. Jaggars et al. (2013) found a failure rate of 25% in online math courses with community college students. The failure rate of 34.6% of the students in the present study indicates that this particular convenience sample exhibited very high failure rates. In particular, the failure rate of the College Algebra course was 36.7%. While the present study did not consider factors related to placement in math courses, perhaps some students are placed in courses without having the necessary skills to succeed.

Academic Risk Factors' Relationship to Academic Performance

The present study hypothesized that academic risk factors such as gender, ethnicity, high school graduation status, and age would have a relationship to academic performance. However, no significant correlations were found. Moreover, these academic risk factors did not contribute any unique variance as predictors of academic performance in the regression model. This result is consistent with research findings of no significant correlations between age, gender, and ethnicity and academic performance in community college online courses (Jost et al., 2012). Jost, Rude-Parkins, and Githens (2012) found that a cumulative GPA is the only predictor of academic performance when controlled for in a multiple regression analysis that includes demographic independent variables. The present study used high school graduation status as a proxy for prior academic success but no correlation to academic performance was found.

The present study showed no statistical differences between males and females in academic performance. This result was surprising given that research on educational outcomes for females shows that females are more likely to graduate from high school and are more likely to earn a college degree (Buchmann & DiPrete, 2006; Heckman & LaFontaine, 2010). However, this community college setting has a disproportionate population of underprepared students, which likely impacts educational outcomes.

Despite the fact that the diversity of the convenience sample in this study was over 63% non-white, no significant differences in academic success were found for ethnicity. This was surprising given that there is ample empirical evidence that students of color have far fewer degrees conferred compared to white students and that they have been systematically disadvantaged in school (DuBrock, 2000; NCES, 2004). One possible explanation is that underprepared white students in a community college setting do not exhibit the same levels of academic persistence or success as their white counterparts in a four-year college setting.

The current study hypothesized that age would have a relationship to academic performance because older students may exhibit more maturity, persistence, self-regulation, and better executive functioning. However, no evidence was found to correlate age with academic performance. This is contrary to Wladis et al.'s (2015) finding showing that older, male students performed better than other students. The present study did not include data on employment or family obligations, factors which potentially diminish any social or cognitive advantages associated with age.

Self-Regulation Beliefs as a Moderator of Academic Risk Factors

Numerous studies have explored the relationship between self-regulated learning and academic performance (Agustiani et al., 2016; Barnard-Brak et al., 2010; Cazan, 2014; Pardo et al., 2016; Puzziferro, 2008). Ning and Downing (2012) explored the moderating effects of self-regulation and motivation on learning experience for predicting academic performance and found positive and significant effects. The present study is unique because it explored the hypothesis that self-regulation beliefs would significantly moderate the relationship of academic risk factors to academic performance.

The moderating effects of Self-Efficacy for Learning and Performance and Task Value were regressed to three academic risk factors. Regression analyses of Self-Efficacy for Learning and Performance did not show significant moderating effects. However, the regressed interaction effect of Self-Efficacy for Learning and Performance and gender did explain slightly more (2.5%) of the variance accounted for in the regression model. This result indicates the possibility of an interaction effect, but the small sample size did not reveal any meaningful significance. Given that the academic risk factors were not found to be predictors of academic success, it was not surprising that self-regulation moderation was minimal.

Limitations

The present study was conducted in a community college setting contextualized by a convenience sample population consisting of students in online mathematics courses. Therefore, the results of this study lack certain requirements of external validity and are limited to this setting. The following are limitations that should also be considered when applying the findings of this research to other contexts.

1. Convenience Sample Size and Characteristics

The present research relied on the cooperation and collaboration of two instructors in an authentic educational setting. Choosing to conduct the research in this setting limited the ability to recruit participants and collect relevant data. The final convenience sample consisted of 53 responses from three different online mathematics courses. Despite the relatively small *n* of the study, the response rate of 63% provided a reasonable representation of the overall population in the three online mathematics courses (Gall et al., 2015). The design of the research included eight independent variables for analysis using hierarchical multiple regression. A range of 10–15 samples per independent variable is generally expected for a multiple regression analysis, suggesting that the present study needed a minimum of 80 participants for the sample (Fields, 2014). However, using a multi-step hierarchical multiple regression analysis enabled identification of the relative contribution of known variances of each group of self-regulation variables and academic risk variables in the model. Additionally, only two subscale variables were regressed to academic risk variables to determine moderating effects to academic performance.

Moreover, since the measurement of self-regulation is not defined by a particular discipline or instructional context, the results of this study are generalizable only to this particular convenience sample in this specific learning environment. Despite the convenience sample limitations, the current research does provide limited insight into the performance of community college students taking online mathematics courses, which has been the subject of only a limited number of empirical studies.

2. MSLQ Self-Report Questionnaire

The MSLQ questionnaire is a valid and reliable instrument designed to measure self-regulation perceptions (Duncan & McKeachie, 2005; Pintrich et al., 1993). However, the use of this instrument in the present study has several limitations. First, while the MSLQ questionnaire is widely used to measure self-regulation in online learning environments, it is not specifically designed for this learning environment (Duncan & McKeachie, 2005; Pintrich et al., 1993). Furthermore, the questions in the current study were not modified in order to maintain the validity and reliability of the instrument. Second, the results of any self-report questionnaire are inherently limited due to the potential bias of the respondents, and therefore, potentially not valid or reliable (Gall et al., 2015). However, Duncan and McKeachie (2005) have sufficiently refuted this potential bias with this instrument in their research. Third, the present study selected only a subset of the full questionnaire including only four of the fifteen self-regulation subscales and 30 of the 81 questions contained in the complete questionnaire. However, the questionnaire was developed to be modular, and the developers maintain that the use of subcomponents of the instrument retains its validity and reliability (Pintrich et al., 1993). The selection of subscales for inclusion in this study was strategic and based on the highest reported correlations to academic performance. Additionally, the decision to use a subset of the questionnaire was justified in order to increase participant response rates and accuracy of responses by limiting the time to complete the survey to less than seven minutes. Requiring an answer to each question provided by the electronic survey software tool used to administer the questionnaire enhanced response accuracy.

3. Selection Bias in Online Classes

The study's sample was comprised of students who registered for online mathematics courses. Students who registered for the online classes self-selected this learning environment and therefore may already have certain biases about their perceived ability to be successful in an online class. Additionally, the present study did not measure any prior experience or success in online classes that could have been used as an independent variable in the study. However, self-efficacy with online technologies is not necessarily a predictor of future academic success (Puzziferro, 2008). While including a measure of online learning success or mathematics self-efficacy would have been informative, the addition of another independent variable would have necessitated a larger sample size (Gall et al., 2015).

4. Mathematics Software Influencing Self-Regulation

The online mathematics courses in the study utilized two different web-based mathematics programs to manage learning and assessment. The XYZ Homework program used in the Algebra I and II courses is a non-adaptive system, but it provides immediate feedback on task performance and allows teachers to communicate with students using a discussion forum. The ALEKS program used in the College Algebra course uses an artificial intelligence assessment and learning system that utilizes adaptive questioning. ALEKS is built using Knowledge Space Theory, which is a framework that utilizes an algorithm to identify the knowledge state of a learner and creates an individualized learning space (Yilmaz, 2017).

The adaptive features of ALEKS could have potentially provided more support for self-regulation than the XYZ Homework program, thus biasing the results of the MSLQ questionnaire responses. Three questions in the MSLQ questionnaire were identified as potentially revealing a bias in how the ALEKS software potentially influences self-regulation perceptions (see Table 22). A paired-samples t-test was conducted to compare the mean scores of students who used the ALEKS software and students who used the XYZ Homework software. There was no significant difference in the scores for question number 26 $t(47) = 1.631$, $p = 0.1096$. There was no significant difference in the scores for question number 23 $t(47) = 0.332$, $p = 0.7412$. There was no significant difference in the scores for question number 25 $t(47) = 0.625$, $p = 0.5347$. The results indicate that the ALEKS software did not influence or bias the responses to the three questions identified.

Table 22

Comparing ALEKS Mean Response Scores to XYZ Homework Mean Response Scores

MSLQ Question	ALEKS		XYZ Homework	
	M	*SD*	*M*	*SD*
26. When studying for this course I try to determine which concepts I don't understand well	5.10	1.744	5.76	1.091
23. When course work is difficult, I either give up or only study the easy parts	5.30	1.593	5.45	1.526
25. Even when course materials are dull and uninteresting, I manage to keep working until I finish.	5.50	1.318	5.72	1.131

5. Prior Feedback that Influenced Self-Regulation Responses

Students completed the MSLQ questionnaire between weeks two and four of the quarter. Any instructor feedback or other assessment of their work potentially biased their responses to the questionnaire and, in particular, to the Self-Efficacy for Learning and Performance subscale. Instructor feedback and assessment data were not included in the scope of the present study.

Implications

As community colleges continue to expand online mathematics course offerings that serve as gateways to career pathways, the potential for the study habits, motivation, and learning skills associated with self-regulation to influence academic success increases (Xu & Jaggars, 2014). In the present study, 42.9% of the students had a final mathematics test score of less than 75%, with nine of the students either receiving a score of zero or withdrawing from the course. These data suggest that a significant number of students potentially failed their mathematics course. This result is consistent with the findings at the Columbia University Community College Research Center, which concluded developmental mathematics courses had a failure/withdrawal rate of 62% in online courses versus 43% in face-to-face courses (Jaggars et al., 2013). Bahr (2011) also found that a majority of students who enroll in remedial courses in community colleges do not attain a college competency level. Given that passing mathematics courses is a prerequisite for many career pathways, failure can prevent students from advancing in certain programs and ultimately not attaining a credential, certification, or degree required for employment.

Research has shown that self-regulation can influence academic outcomes in online courses (Agustiani et al., 2016; Puzziferro, 2008). The findings of the current study suggest that the motivational subscales of Task Value and Self-Efficacy for Learning and Performance potentially influence academic outcomes. While self-regulation is only one factor attributed to success in online courses, supporting students' self-regulation skills can be achieved with moderate adjustments to course design and with instructional modifications such as increased course scaffolding. More support for underprepared students in the community college setting is essentially a matter of justice and equity.

Future Research

This study considered only four of the fifteen available subscales of the MSLQ questionnaire survey instrument. These four subscales were selected based on prior research indicating a strong correlation to academic performance (Pintrich et al., 1993). Investigation of the relationship of all the subscales on the MSLQ questionnaire to determine which subscales are most relevant to specific contextualized learning environments warrants further research. A study that includes all fifteen subscales and the complete 81-question survey would provide a more comprehensive analysis of the role of self-regulation in online learning. Additionally, researchers should also consider using the modified MSLQ survey, which has been adapted to include contextualized terms specific to online learning.

The present study focused exclusively on online mathematics courses in a community college setting. As community colleges continue to expand general online course offerings, more research is needed in all disciplines to investigate the role self-regulated learning plays in academic achievement. Such research is especially important to courses that are considered “gatekeepers” that are often viewed as barriers, which limit long-term academic success and degree completion.

Academic risk factors could play an important role in identifying student characteristics associated with self-regulation and academic success. Bean and Metzner (1985) identified students over the age of 24 as a group highly susceptible to attrition. While the present study did not find a significant relationship between academic risk factors and academic achievement, prior research has suggested such a relationship exists (National Center for Educational Research, 2000; Wladis, Conway, & Hachey, 2015). Moreover, research that investigates how self-regulation moderates English language proficiency, prior experience with online learning success, or prior success in mathematics courses could provide guidance for predicting academic performance of underprepared students.

This study relied on self-reported beliefs demonstrated in the MSLQ questionnaire’s responses to measure self-regulation. Prior research suggests that self-regulation skills can be taught and provided as an effective intervention (Bol et al., 2016; Hu & Driscoll, 2013; Zheng, 2016). Research that investigates self-regulation skills that are taught as an intervention measure may limit the bias of self-reported self-regulation skills by combining it with other ways of determining student self-regulation.

Recommendations

Certain empirical data suggest that self-regulation could play a role in student success in online courses (Xu & Jaggars, 2014). While the present study suggests a relationship between Task Value and Self-Efficacy for Learning and Performance to academic performance, numerous prior studies have found that self-regulation can influence academic outcomes (Agustiani et al., 2016; Barnard-Brak et al., 2010; Cazan, 2014; Pardo et al., 2016; Puzziferro, 2008). Educators developing online courses should consider incorporating course design features and tools that promote self-regulation as a way to support student success. The following are recommendations for administrators and instructors who design or teach online courses.

1. Survey Student Self-Regulation Beliefs

The MSLQ questionnaire used in the present study could be administered to all students who register for an online course to measure student self-regulation beliefs. Instructors could survey all fifteen subscales or select subscales they wish to measure that are particularly applicable to the student population or contextual subject of the course. The results of the survey could be used to identify motivation or skills of self-regulation that individual students may need.

For example, intrinsic goal orientation is a subscale of the MSLQ that is correlated (r = .25) with academic performance (Pintrich et al., 1993). Students who have a low score on this subscale could be encouraged to set goals related to the course that consider ways in which the course content would be meaningful to them independent of the grade or college requirements. Goal setting has shown strong promise as an educational intervention (Hattie, 2012). Instructors could incorporate an assignment for students to complete of setting intrinsic goals before the course begins.

Time and study environment is another MSLQ subscale that correlates (r = .28) to academic performance (Pintrich et al., 1993). Students who score in the bottom quartile of this subscale may need support with scaffolding assignments and workload or advice on how to establish a study environment that is organized, quiet, and free from visual and auditory distractions. Instructors who identify students with this self-regulation weakness could develop coursework with more scaffold support and provide students with suggestions on how to create or seek out study environments more conducive to learning.

2. Evaluate and Analyze Online Course Software that Addresses Self-Regulation Motivation and Learning Skills

The present study acknowledged, but did not measure, the differences between the two software programs used by instructors in the courses considered in this study. Instructors should consider how features of the learning software address self-regulation motivation and skills.

Instructors could also incorporate self-regulation components into course design with learning management systems. For example, the learning strategy Metacognitive Self-Regulation is an MSLQ subscale that is correlated (r = .30) to academic performance (Pintrich et al., 1993). Reflection is a practice that has been shown to have a positive effect size on learning (Hattie, 2012). Having students reflect on their learning as a required component of assignments can promote Metacognitive Self-Regulation.

3. Incorporate Training in Self-Regulation Learning in Courses

Evidence has shown that self-regulation skills can be taught and used to support students in online learning environments (Bol et al., 2016; Hu & Driscoll, 2013. Instructors could incorporate web-based training in self-regulation learning skills into their existing courses as a requirement or supplement.

Conclusion

As community colleges continue to expand online course offerings, it is imperative that administrators and instructors understand the factors associated with student success in this contextualized learning environment. Prior research has identified self-regulation as an important factor in academic success in online courses (Agustiani et al., 2016; Barnard-Brak et al., 2010; Cazan, 2014; Pardo et al., 2016; Puzziferro, 2008). The current study contributes to the empirical body of literature regarding the role self-regulated learning plays in academic achievement within the context of community college online mathematics courses. The findings of this study suggest that the self-regulation subscales of Self-Efficacy for Learning and Performance and Task Value appear to relate to academic performance in this specific contextualized learning environment. In addition, this study makes a unique contribution to research regarding the moderating effects of self-regulated learning on academic risk factors related to academic performance in online courses.

References

Agustiani, H., Cahyad, S., & Musa, M. (2016). Self-efficacy and self-regulated learning as predictors of students' academic performance. *The Open Psychology Journal*, *9*(1), 1-6. http://dx.doi.org/10.2174/1874350101609010001

Allen, I., & Seaman, J. (2016). *Online report card: Tracking online education in the United States.* Retrieved from Online Learning Consortium website: https://onlinelearningconsortium.org/

Allen, I., & Seaman, J. (2017). *Digital learning compass: Distance education enrollment report 2017*. Retrieved from Online Learning Consortium website: https://onlinelearningconsortium.org/

American Association of Community Colleges (2016). *Fast facts.* Retrieved from https://www.aacc.nche.edu/

American Association of Community Colleges (2018). *Fast facts.* Retrieved from https://www.aacc.nche.edu/

Ashby, J., Sadera, W., & McNary, S. (2011). Comparing student success between developmental mathematics courses offered online, blended, and face-to-face. *Journal of Interactive Online Learnin*g, *10*(3), 128-140. Retrieved from https://www.learntechlib.org

Baath, J. A. (1985). A note on the origin of distance education. *ICDE Bulletin*, *7*, 61-62.

Bahr, P. (2008). Does mathematics remediation work?: A comparative analysis of academic attainment among community college students. *Research in Higher Education*, *49*(5), 42-450.

Bahr, P. (2011). Deconstructing remediation in community colleges: Exploring associations between course-taking patterns, course outcomes, and attrition from the remedial mathematics and remedial writing sequences. *Research in Higher Education*, *53*(6), 661-693. https://dx.doi.org/10.1007/s11162-011-9243-2

Bailey, T., Jaggars, S., & Jenkins, D. (2015). *Redesigning America's community colleges.* Cambridge, MA: Harvard University Press.

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

Bandura, A. (1986). The explanatory and predictive scope of self-efficacy theory. *Journal of Social and Clinical Psychology, 4*(3), 359-373. https://dx.doi.org/10.1521/jscp.1986.4.3.359

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes, 50*(2), 248-287. https://dx.doi.org/10.1016/0749-5978(91)90022-L

Barbules, N., & Callister, T. (2000). Universities in transition: The promise and challenge of new technologies. *Teachers College Record*, *102*(2), 271-293.

Barnard-Brak, L., Lan, W., & Paton, V. (2010). Profiles in self-regulated learning in the online learning environment. *The International Review of Research in Open and Distributed Learning*, *11*(1), 61-80. http://dx.doi.org/10.19173/irrodl.v11i1.769

Bean, J., & Metzner, B. (1985). A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research*, *55*(4), 485-540 https://dx.doi.org/10.3102/00346543055004485

Bernard, R., Abrami, P., Lou, Y., Borokhovski, E., Wade, A., Wozney, L,…Wallet, P. (2004). How does distance education compare with classroom instruction: Meta-analysis of the empirical literature. *Review of Educational Research*, *74*(3), 379-439. https://dx.doi.org/10.3102/00346543074003379

Bol, L., Campbell, D. Y., Perez, T., & Yen, C. (2016). The effects of self-regulated learning training on community college students' metacognition and achievement in developmental mathematics courses. *Community College Journal of Research and Practice*, *40*(6), 480-495. https://dx.doi.org/10.1080/10668926.2015.1068718

Bragg, D. (2012). Appendix C: Two-year college mathematics and student progression in STEM programs of study. In S. Olson & J. Labov (Eds.), *Community colleges in the evolving STEM education landscape.* Washington, DC: National Academic Press.

British Open University (2017). *Annual report 2016/2017*. Retrieved from http://www.open.ac.uk/about/main/sites/files/ecms/web-content/about-annual-report-16-17.pdf

Buchmann, C., & DiPrete, T. (2006). The growing female advantage in college completion: The role of family background and academic achievement. *American Sociological Review*, *71*(4), 515-541. doi:10.1177/000312240607100401

Carnegie (2015). *Carnegie classification of institutions of higher education. [Data file.* Retrieved from http://carnegieclassifications.iu.edu/index.php

Carnevale, A., Strohl, J., & Ridley, N. (2017). *Good jobs that pay without a ba: A state by state analysis[Data file]*. Retrieved from Center on Education and the Workforce website: https://goodjobsdata.org/

Cazan, A. (2014). Self-regulated learning and academic achievement in the context of online learning environments. *Proceedings of the 10th International Scientific Conference eLearning and Software for Education.* Retrieved from http://proceedings.elseconference.eu/

Chang, M. (2007). Enhancing web-based language learning through self-monitoring. *Journal of Computer Assisted Learning*, *23*(3), 187-196. http://dx.doi.org/10.1111/j.1365-2729.2006.00203.x

Cho, M., & Heron, M. (2015). Self-regulated learning: The role of motivation, emotion, and use of learning strategies in students' learning experiences in a self-paced online mathematics course. *Distance Education*, *36*(1), 80-99. http://dx.doi.org/10.1080/01587919.2015.1019963

Cohen, J. (1983). The cost of dichotomization. *Applied Psychological Measurement*, *7*(38), 249-253. http://dx.doi.org/10.1177/014662168300700301

Cox, R. D. (2005). Online education as institutional myth: Rituals and realities at community colleges. *Teachers College Record*, *107*(8), 1754-1787.

Cuban, L. (2001). *Oversold & underused*. Cambridge, MA: Harvard University Press.

Daniel, J. (1983). Worldwide trends in distance education: New technologies for interaction. In L. Parker & C. Olgren (Eds.), *Teleconferencing and electronic communications II: Applications, technologies, and human factors* (pp. 392–396). Madison, WI: University of Wisconsin-Extension.

Diehl, W. (2013). Charles Wedemeyer: Visionary pioneer of distance education. In M. G. Moore (Ed.), *Handbook of distance education* (pp. 38-48). New York, NY: Routledge.

DuBrock, C. (2000, May). *Financial aid and college persistence: A five-year longitudinal study of 1993 and 1994 beginning freshmen students.* Paper presented at the Annual Forum of the Association for Institutional Research, Cincinnati, OH.

Duncan, T., & McKeachie, W. (2005). The making of motivated strategies for learning questionnaire. *Educational Psychologist*, *40*(2), 117-128. http://dx.doi.org/10.1207/s15326985ep4002_6

Faul, F., Erdfelder, E., Lang, A., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175-191. https://dx.doi.org/10.3758/BF03193146

Fields, A. (2014). *Discovering statistics using IBM SPSS statistics*. Los Angeles, CA: Sage.

Fincham, J. E. (2008). Response rates and responsiveness for surveys, standards, and the journal. *American Journal of Pharmaceutical Education School of Pharmacy, 72*(2), 43. https://dx.doi.org/10.5688/aj720243

Fink, A. (1995). *How to sample in surveys*. Thousand Oaks, CA: Sage.

Fowler, F. (2014). *Survey research methods* (5th ed.). Thousand Oaks, CA: Sage.

Friedman, T. (2016). *Thank you for being late.* New York, NY: Picador.

Gall, M. D., Gall, J. P., & Borg, W. (2015). *Applying educational research*. Boston, MA: Pearson.

Garrison, D. R. (1985). Three generations of technological innovation in distance education. *Distance Education, 6*(2), 235-241. https://dx.doi.org/10.1080/0158791850060208

Garrison, D. R., & Baynton, M. (1987). Beyond independence in distance education: The concept of control. *The American Journal of Distance Education*, *1*(3), 3-15. https://dx.doi.org/10.1080/08923648709526593

Grice, P. (1989). *Studies in the way of words*. Cambridge, MA: Harvard University Press.

Hannafin, M., Land, S. M., & Oliver, K. (1999). Open learning environments: foundations, methods, and models. In C. M. Reigeluth (Ed.), *Instructional design theories and models* (pp. 115–140). Mahwah, NJ: Lawrence Erlbaum Associates.

Hattie, J. (2012). *Visible learning for teachers: Maximizing impact on learning*. New York, NY: Routledge.

Heckman, J., & LaFontaine, P. (2010). The American high school graduation rate. *Review of Economics and Statistics*, *92*(2), 244-262. https://dx.doi.org/10.1162/rest.2010.12366

Hodges, C. (2008). Self-efficacy in the context of online learning environments. *Performance Improvement Quarterly*, *20*(3-4), 7-25. http://dx.doi.org/10.1002/piq.20001

Horn, L., & Nevill, S. (2006). *Profile of undergraduates in U.S. postsecondary education institutions: 2003-2004 with a special analysis of community college students.* U.S. Department of Education. Retrieved from https://files.eric.ed.gov/fulltext/ED491908.pdf

Hu, H., & Driscoll, M. (2013). Self-regulation in e-learning environments: A remedy for community college? *Educational Technology & Society*, *16*(4), 171-184.

Internet Society. (2013). *Brief history of the internet*. Retrieved from http://www.internetsociety.org/internet/what-internet/historyinternet/ brief-history-internet

Jaggars, S., & Bailey, T. (2010). *Effectiveness of full online courses for college students: Response to a department of education meta-analysis.* Retrieved from Teachers College, Columbia University Community College Research Center website: https://ccrc.tc.columbia.edu/publications/effectiveness-fully-online-courses.html

Jaggars, S., Edgecombe, N., & Stacey, G. (2013). *What we know about online course outcomes.* Retrieved from Teachers College, Columbia University Community College Research Center website: https://ccrc.tc.columbia.edu/publications/what-we-know-online-course-outcomes.html

Jost, B., Rude-Parkins, C., & Githens, R. (2012). Academic performance, age, gender, and ethnicity in online courses delivered by two-year colleges. *Community College Journal of Research and Practice*, *36*(9), 656-669. https://dx.doi.org/10.1080/10668921003744876

Kauffman, D., Ge, X., Xui, X., & Chen, C. (2008). Prompting in web-based environments: Supporting self-monitoring and problem solving skills in college students. *Journal of Educational Computing Research, 38*(2), 115-137. https://dx.doi.org/10.2190/EC.38.2.a

Kearsley, G. P., Hunter, B., & Seidel, R. J. (1983). Two decades of CBI research: What have we learned? *T.H.E. Journal, 10*(3), 90-94.

Keegan, D. (1980). *Foundations of distance education*. London, England: Routledge.

Lynch, R., & Dembo, M. (2004). The relationship between self-regulation and online learning in a blended learning context. *The International Review of Research in Open and Distance Learning*, *5*(2), 1-16. http://dx.doi.org/10.19173/irrodl.v5i2.189

Mayer, R. E. (2014). Principles based on social cues in multimedia learning: Personalization, voice, image, and embodiment principles. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (pp. 345-368). New York, NY: Cambridge University Press.

McClain, E. (2015). *The effects of the use of a self-monitoring form on achievement and self-regulated learning in a developmental mathematics course* (Doctoral dissertation). Retrieved from https://kuscholarworks.ku.edu/

McMahon, M. & Oliver, R. (2001). Promoting self-regulated learning in an on-line learning environment. *Proceedings of the World Conference on Educational Multimedia, Hypermedia & Telecommunication.* Retrieved from https://www.learntechlib.org/j/EDMEDIA/

Means, B., Toyama, Y., Murphy, R., Bakia, M., & Jones, K. (2009). *Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies*. Washington DC: U.S. Department of Education. Retrieved from https://www.sri.com/work/publications/evaluation-evidence-based-practices-online-learning-meta-analysis-and-review-onlin

Means, B., Toyama, Y., Murphy, R., & Bakia, M. (2013). *The effectiveness of online and blended learning: A meta-analysis of the empirical literature.* Retrieved from the Teachers College Website https://www.tcrecord.org/content.asp?contentid=16882

Moore, J. L., Dickson-Dean, C., & Gaylen, K. (2010). E-learning, online learning, and distance learning environments: Are they the same? *Internet and Higher Education*, *14*, 129-135.

Moore, M. G. (1972). Learner autonomy: The second dimension of independent learning. *Convergence*, *5*(2), 76-88.

Moore, M. G. & Kearsley, G. (1996). *Distance education: A systems view*. Belmont, CA: Wadsworth.

National Center for Education Statistics. (2002). *Postsecondary attainment: Differences by socioeconomic status*. The Education Longitudinal Study of 2002 (ELS:2002). [Data file]. Retrieved from https://nces.ed.gov/programs/coe/indicator_tva.asp

National Center for Education Statistics. (2004). *Table 25.1. Number and percentage distribution of degrees conferred by degree-granting institutions, by level of degree, race/ethnicity, and sex: 2003-04.* [Data file]. Retrieved from https://nces.ed.gov/pubs2007/minoritytrends/tables/table_25_1.asp?referrer=report

National Center for Education Statistics. (2014). *Fast facts*. [Data file]. Retrieved from https://nces.ed.gov/programs/digest/d15/tables/dt15_311.22.asp?current=yes

National Center for Education Statistics. (2015a). *Fast facts.* [Data file]. Retrieved from https://nces.ed.gov/fastfacts/display.asp?id=76

National Center for Education Statistics. (2015b). *Total fall enrollment in degree-granting postsecondary institutions, by level and control of institution, attendance status, and sex of student: Selected years, 1970 through 2023. Table 303.30* [Data file]. Retrieved from https://nces.ed.gov/programs/digest/d13/tables/dt13_303.30.asp

National Center for Education Statistics. (2017).. *Average undergraduate tuition, fees, room, and board rates for full-time students in degree-granting postsecondary institutions, by percentile of charges and control and level of institution: Selected years, 2000-01 through 201. Table 330.30* [Data file]. Retrieved from https://nces.ed.gov/programs/digest/d16/tables/dt16_330.30.asp?current=yes

Ning, H., & Downing, K. (2012). Influence of student learning experience on academic performance: The mediator and moderator effects of self-regulation and motivation. *British Educational Research Journal*, *38*(2), 219-237. https://dx.doi.org/10.1080/01411926.2010.538468

Noble, D. F. (2001). *Digital diploma mills. The automation of higher education*. New York, NY: Monthly Review Press.

Olson, S., & Labov, J. (2012). *Community colleges in the evolving stem education landscape: Summary of a summit.* Retrieved from the Washington, DC: National Academies Press https://www.nap.edu/

Online Learning Consortium. (2017). *Our history*. Retrieved from https://onlinelearningconsortium.org/about/history/

Pappano, L. (2012, November 2). The year of the mooc. *The New York Times*. Retrieved from http://www.nytimes.com

Pardo, A., Han, F., & Ellis, R. (2016). Combining university student self-regulated learning indicators and engagement with online learning events to predict academic performance. *IEEE Transactions on Learning Technologies*, *10*(1), 82-92. https://dx.doi.org/10.1109/TLT.2016.2639508

Peterman, D. (2000). First-generation college students. *Community College Journal of Research and Practice*, *24*(5), 417-420.

Pintrich, P., & De Groot, E. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, *83*(1), 33-40. http:// dx.doi:10.1037/0022-0663.82.1.33

Pintrich, P., Smith, D., Garcia, T., & McKeachie, W. (1991). *A manual for the use of the motivated strategies for learning questionnaire (MSLQ)*. Retrieved from https://eric.ed.gov

Pintrich, P., Smith, D., Garcia, T., & McKeachie, W. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire (MSLQ). *Educational and Psychological Measurement*, *53*(3), 801-813. https://dx.doi.org/10.1177/0013164493053003024

Pittman, V. (2013). University correspondence study: A revised histographic perspective. In M. G. Moore (Ed.), *Handbook of distance education* (pp. 21-37). New York, NY: Routledge.

Provasnik, S., & Planty, M. (2008). *Community colleges: Special supplement to the condition of education 2008. [Data file]. Retrieved from the* National Center for Education Statistics https://nces.ed.gov/pubs2008/2008033.pdf

Puzziferro, M. (2008). Online technologies self-efficacy and self-regulated learning as predictors of final grade and satisfaction in college-level online courses. *American Journal of Distance Education, 22*(2), 72-89. http://dx.doi.org/10.1080/08923640802039024

Quarles, C., & Davis, M. (2017). Is learning in developmental math associated with community college outcomes? *Community College Review*, *45*(1), 33-51. https://dx.doi.org/10.1177/0091552116673711

Rowe F., & Rafferty, J. (2013). Instructional design interventions for supporting self-regulated learning: Enhancing academic outcomes for postsecondary e-learning environments. *Journal of Online Learning and Teaching*, *9*(4), 590-601.

Saba, F., & Shearer, R. (1994). Verifying key theoretical concepts in a dynamic model of distance education. *American Journal of Distance Education*, *8*(1), 36-59. https://dx.doi.org/10.1080/08923649409526844

Saba, F. (2013). Building the future: A theoretical perspective. In M. G. Moore (Ed.), *Handbook of distance education* (pp. 49-65). New York, NY: Routledge.

Seaman, J., Allen, I., & Seaman, J. (2018). *Grade increase: Tracking distance education in the United States.* Retrieved from Online Learning Consortium website: https://onlinelearningconsortium.org/

Seattle Pacific University. (2012). *IRB user's guide.* Retrieved from: https://spu.edu/~/media/university-leadership/provost/documents/IRB%20User%20Guidelines%20101117.ashx

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

Stack, S. (2015). Learning outcomes in an online vs traditional course. *International Journal for the Scholarship of Teaching and Learning*, *9*(1), 1-18. Retrieved from http://hdl.handle.net/TVDHQB_123456789/820

Sumner, J. (2000). Serving the system: A critical history of distance education. *Open Learning*, *15*(3), 267-285.

Vogt, W., & Johnson, R. (2016). *The Sage dictionary of statistics & methodology*. Thousand Oaks, CA: Sage.

Walton, R. (2011) *Learning at a distance: Undergraduate enrollment in distance education courses and degree programs (NCES 2012-154)*. Washington, DC: Government Printing Office.

Wang, C., Shannon, D., & Ross, M. (2013). Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education*, *34*(3), 302-323. http://dx.doi.org/10.1080/01587919.2013.835779

Wang, X., Wang, Y., Wickersham, K., Sun, N., & Chan, H. (2017). Math requirements fulfillment and educational success of community college students: A matter of when. *Community College Review*, *45*(2), 99-118. https://dx.doi.org/10.1177/0091552116682829

Weinstein, C. E., & Underwood, V. L. (1985). Learning strategies: The how of learning. In J. W. Segal, S. F. Chipman, & R. Glaser (Eds.), *Thinking and learning skills:*

Relating instruction to research (pp. 241–258). Hillsdale, NJ: Lawrence Erlbaum Associates.

Weinstein, C., & Mayer R. (1986). The teaching of learning strategies. In M. Wittrock (Ed.), *Handbook of research on teaching* (pp. 315-327). New York, NY: Macmillan.

Wigfield, A., & Eccles, J. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology*, *25*(1), 68-81. https://dx.doi.org/10.1006/ceps.1999.1015

Wijekumar, K., Ferguson, L., & Wagoner, D. (2006). Problems with assessment validity and reliability in web-based distance learning environments and solutions. *Journal of Educational Multimedia and Hypermedia*, *15*(2), 199-215.

Wladis, C., Conway, K., & Hachey, A. (2015). The online stem classroom- who succeeds? An exploration of the impact of ethnicity, gender, and non-traditional student characteristics in the community college context. *Community College Review*, *43*(2), 142-164. https://dx.doi.org/10.1177/0091552115571729

Xu, D., & Jaggars, S. (2014). Performance gaps between online and face-to-face courses: Differences across types of students and subject areas. *Journal of Higher Education*, *85*(5), 633-659. https://dx.doi.org/10.1080/00221546.2014.11777343

Xu, D., & Dadgar, M. (2018). How effective are community college remedial math courses for students with the lowest math skills? *Community College Review*, *46*(1), 62-81. https://dx.doi.org/10.1177/0091552117743789

Yilmaz, (2017). *Effects of adaptive learning technologies on mathematics achievement: A quantitative study of ALEKS mathematics software* (Doctoral dissertation). Retrieved from http://proquest.com

Yu, H. (2017). Factors associated with student academic achievement at community colleges. *Journal of College Student Retention: Research, Theory & Practice*, *19*(2), 224-239. https://dx.doi.org/10.1177/1521025115612484

Zavarella, C. A. (2008). *Computer-based instruction and remedial mathematics: A study of student retention at a Florida community college* (Doctoral dissertation). Retrieved from http://proquest.com

Zhao, Y., Lei, J., Yan, B., Lai, C., & Tan, H. (2005). What makes the difference? A practical analysis of research on the effectiveness of distance education. *Teachers College Record*, *107*(8), 1836-1884. Retrieved from https://www.tcrecord.org

Zheng, L. (2016). The effectiveness of self-regulated learning scaffolds on academic performance in computer-based learning environments: A meta-analysis. *Asia Pacific Education Review*, *17*(2), 187-202. https://dx.doi.org/10.1007/s12564-016-9426-9

Zimmerman, B. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology*, *81*(3), 329-339. http://dx.doi.org/10.1037/0022-0663.81.3.329

Zimmerman, B. J. (2000). Attainment of self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13-39). San Diego, CA: Academic Press.

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, *41*(2), 64-70. https://dx.doi.org/10.1207/s15430421tip4102_2

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and prospects. *American Educational Research Journal*, *45*(1) 166-183. https://dx.doi.org/10.3102/0002831207312909

Zimmerman, B. J., & Martinez-Pons, M. (1990). Student differences in self-regulated learning: Relating grade, sex, and giftedness to self-efficacy and strategy use. *Journal of Educational Psychology*, *82*(1), 51-59. http://dx.doi.org/10.1037/0022-0663.82.1.51

.

Appendix A: MSLQ Questionnaire Item Descriptive Analysis

Task Value Items	*N*	*Min.*	*Max.*	*M*	*SD*
I think I will be able to use what I learn in this course in other courses.	49	2	7	5.82	1.33
It is important for me to learn the course material in this class.	49	3	7	6.49	.91
I am very interested in the content area of this course.	49	1	7	4.73	1.91
I think the course material in this class is useful for me to learn.	49	2	7	5.65	1.48
I like the subject matter of this course.	49	1	7	4.65	1.94
Understanding the subject matter of this course is very important to me.	49	2	7	5.88	1.31

Self-Efficacy for Learning and Performance Items	*N*	*Min.*	*Max.*	*M*	*SD*
I believe I will receive an excellent grade in this class.	49	1	7	4.55	1.68
I'm certain I can understand the most difficult material presented in the readings for this course.	49	1	7	4.31	1.82

I'm confident I can learn the basic concepts taught in this course.	49	1	7	5.73	1.18
I'm confident I can understand the most complex material presented by the instructor in this course.	49	3	7	4.76	1.64
I'm confident I can do an excellent job on the assignments and tests in this course.	49	1	7	4.59	1.68
I expect to do well in this class.	49	1	7	5.14	1.69
I'm certain I can master the skills being taught in this class.	49	1	7	4.94	1.62
Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.	49	1	7	4.94	1.56

Metacognitive Self-Regulation Items	*N*	*Min.*	*Max.*	*M*	*SD*
During class time I often miss important points because I'm thinking of other things.	49	1	7	4.96	1.79
When reading for this course, I make up questions to help focus my reading.	49	1	7	3.33	2.17
When I become confused about something I'm reading for this class, I go back and try to figure it out.	49	1	7	6.22	1.08
If course readings are difficult to understand, I change the way I read the material.	49	1	7	5.39	1.63
Before I study new course material thoroughly, I often skim it to see how it is organized.	49	1	7	4.67	1.87
I ask myself questions to make sure I understand the material I have been studying in this class.	49	1	7	4.76	1.73
I try to change the way I study in order to fit the course requirements and the instructor's teaching style.	49	1	7	4.88	1.77
I often find that I have been reading for this class but don't know what it was all about.	49	1	7	4.65	1.85
I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over	49	1	7	4.71	1.5

when studying for this course.					
When studying for this course I try to determine which concepts I don't understand well.	49	1	7	5.49	1.41
When I study for this class, I set goals for myself in order to direct my activities in each study period.	49	1	7	4.80	1.63
If I get confused taking notes in class, I make sure I sort it out afterwards.	49	1	7	4.76	1.99

Effort Regulation Items	*N*	*Min.*	*Max.*	*M*	*SD*
I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do.	49	2	7	5.37	1.66
I work hard to do well in this class even if I don't like what we are doing.	49	1	7	5.63	1.46
When course work is difficult, I either give up or only study the easy parts.	49	2	7	5.39	1.53
Even when course materials are dull and uninteresting, I manage to keep working until I finish.	49	3	7	5.63	1.20

Self-Regulation Student Survey

This survey is being conducted for educational research purposes. The results of your responses will be anonymous and confidential.
Please rate the following items based on your behavior in this class.

Your rating should be on a 7-point scale where 1 = Not at all true of me to 7 = Very true of me ."

* 1. Please enter your South Student ID (SID)

(All survey results are anonymous and confidential)

2. Which math course are you currently enrolled in?

- Math 084 (Algebra I)
- Math 085 (Algebra II)
- Math 102 (College Algebra)

3. I think I will be able to use what I learn in this course in other courses.

Not at all true of me — Very true of me

4. I believe I will receive an excellent grade in this class.

Not at all true of me — Very true of me

5. I'm certain I can understand the most difficult material presented in the readings for this course.

Not at all true of me — Very true of me

6. It is important for me to learn the course material in this class.

Not at all true of me — Very true of me

7. I'm confident I can learn the basic concepts taught in this course.

Not at all true of me ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very true of me

8. I'm confident I can understand the most complex material presented by the instructor in this course.

Not at all true of me ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very true of me

9. I am very interested in the content area of this course.

Not at all true of me ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very true of me

10. I'm confident I can do an excellent job on the assignments and tests in this course.

Not at all true of me ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very true of me

11. I expect to do well in this class.

Not at all true of me ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very true of me

12. I think the course material in this class is useful for me to learn.

Not at all true of me ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very true of me

13. I like the subject matter of this course.

Not at all true of me ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very true of me

14. Understanding the subject matter of this course is very important to me.

Not at all true of me ◯ ◯ ◯ ◯ ◯ ◯ ◯ Very true of me

15. I'm certain I can master the skills being taught in this class.

Not at all true of me — Very true of me

16. Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.

Not at all true of me — Very true of me

17. During class time I often miss important points because I'm thinking of other things.

Not at all true of me — Very true of me

18. When reading for this course, I make up questions to help focus my reading.

Not at all true of me — Very true of me

19. I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do.

Not at all true of me — Very true of me

20. When I become confused about something I'm reading for this class, I go back and try to figure it out.

Not at all true of me — Very true of me

21. If course readings are difficult to understand, I change the way I read the material.

Not at all true of me — Very true of me

22. I work hard to do well in this class even if I don't like what we are doing.

Not at all true of me — Very true of me

23. Before I study new course material thoroughly, I often skim it to see how it is organized.

Not at all true of me — Very true of me

○ ○ ○ ○ ○ ○ ○

24. I ask myself questions to make sure I understand the material I have been studying in this class.

Not at all true of me — Very true of me

○ ○ ○ ○ ○ ○ ○

25. I try to change the way I study in order to fit the course requirements and the instructor's teaching style.

Not at all true of me — Very true of me

○ ○ ○ ○ ○ ○ ○

26. I often find that I have been reading for this class but don't know what it was all about.

Not at all true of me — Very true of me

○ ○ ○ ○ ○ ○ ○

27. When course work is difficult, I either give up or only study the easy parts.

Not at all true of me — Very true of me

○ ○ ○ ○ ○ ○ ○

28. I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course.

Not at all true of me — Very true of me

○ ○ ○ ○ ○ ○ ○

29. Even when course materials are dull and uninteresting, I manage to keep working until I finish.

Not at all true of me — Very true of me

○ ○ ○ ○ ○ ○ ○

30. When studying for this course I try to determine which concepts I don't understand well.

Not at all true of me						Very true of me
○	○	○	○	○	○	○

31. When I study for this class, I set goals for myself in order to direct my activities in each study period.

Not at all true of me						Very true of me
○	○	○	○	○	○	○

32. If I get confused taking notes in class, I make sure I sort it out afterwards.

Not at all true of me						Very true of me
○	○	○	○	○	○	○

Below is a sample email message you can use to introduce the survey. Please feel free to modify it to make it more personal. Note I have put in a place where you can enter the points you will award for completing the survey.

Dear students,

I am participating in a research study to learn about the study habits, learning skills, and motivation of students in online math courses. I would like to ask you to participate in this study by completing a short questionnaire. Your answers are anonymous and confidential. The survey is not a test and your answers are not graded. We hope to use the results to help students be successful taking online classes.

If you choose to participate, I can provide you **X** points in this course for your time. Below is a link to the survey. It should take you less than 6 minutes to complete. Please try to complete the survey during the next 5 days.

Thank you,

Seattle Pacific
UNIVERSITY
Engaging the culture, changing the world®

School of Education
3307 Third Avenue West, Suite 202
Seattle, Washington 98119-1950
206 281 2214 phone
206 281 2756 fax
www.spu.edu

September 5, 2017

Subject: IRB Approval – IRB # 171806002 (Exempt Review)

To: Jim Dunnegan

Your research project *"Self regulated learning and academic performance in community college"* has been approved. This study was approved under exempt review as it meets the requirement of "no more than minimal risk" as stated in the *SPU IRB User Guidelines* (2012, p. 5).

Your approval is in effect until what time any methods of the study change substantively. When that occurs, you will need to renew your IRB application. Your study has been assigned IRB number: **171806002.**

Please let me know if I can be of any further support.

Sincerely,

John B. Bond, Ed.D.
SOE IRB Coordinator
Professor of Educational Leadership

171806002
SEP 2017
Expires N/A

Cc: Dr. Arthur Ellis

[redacted]
One of the Seattle Colleges

Office of Planning and Research
[redacted]
Seattle WA

DATE: October 11, 2017

TO: Jim Dunnigan

FROM: Greg Dempsey, Jr.
Chief Data and Strategy Officer [redacted]
Chair of IRB Committee

RE: **Research -** *Self Regulated Learning and Academic Performance in Community College Online Math Courses*

In accordance with [redacted] Policy 530, please accept this memo as official documentation that your IRB application and accompanying materials dated 9/15/2017 for the *Self Regulated Learning and Academic Performance in Community College Online Math Courses* project has been approved.

This approval has been granted through the duration of the project – 3/1/2018. Any additional research activities associated with this project after the project end date, will need to approved accordingly.