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How Student Perceptions of the Online Learning Environment and Student Motivation Predict Persistence, Completion, and Retention in Developmental Mathematics Courses

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HOW STUDENT PERCEPTIONS OF THE ONLINE LEARNING ENVIRONMENT AND STUDENT MOTIVATION PREDICT PERSISTENCE, COMPLETION, AND RETENTION IN DEVELOPMENTAL MATHEMATICS COURSES

by

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ABSTRACT

How Student Perceptions of the Online Learning Environment and Student Motivation Predict Persistence, Completion, and Retention in Developmental Mathematics Courses

by

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Effective online developmental mathematics instruction, that helps students persist through needed coursework and retains students at the university, is essential in the current educational environment. The purpose of this study was to examine how student perceptions of the online learning environment and student motivation predicted course persistence, course completion, and mathematics retention in developmental mathematics courses. This study was a quantitative, non-experimental, and cross-sectional survey design in order to generalize the perceived characteristics of the instructor developed online learning environment.

Participants in this study were 330 undergraduate students enrolled in online developmental mathematics courses during the Fall 2018 semester at eight public universities and colleges in the Utah State Higher Education (USHE) system. Participants completed the Community of Inquiry survey to measure their perceptions of the instructor developed online learning environment. They also completed the MUSIC Model of Motivation survey to measure student motivations toward their online mathematics coursework. The researcher gathered institutional data from the participating universities to measure course persistence, completion and retention. The researcher analyzed the survey data using correlations, multilevel logistic regression and multilevel survival analysis methods.

A multilevel survival analysis and a multilevel logistic regression similarly showed that students perceptions of Success (motivation) and Social Presence (learning environment) factors played a role in predicting student course persistence and completion in online developmental mathematics. A multilevel logistic regression of the measured factors on student retention did not show any significant results.

This finding suggests that efforts and interventions geared towards building student self-efficacy and designing more student-to-student interactions may have the potential to increase course completion rates in online developmental mathematics coursework. Building self-efficacy in online developmental mathematics coursework, and a positive support group of fellow classmates through social presence, has the potential to give students the tools necessary to successfully navigate their own learning.

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PUBLIC ABSTRACT

How Student Perceptions of the Online Learning Environment and Student Motivation Predict Persistence, Completion, and Retention in Developmental Mathematics Courses

Samuel K. Gedeborg

Online developmental mathematics courses have high dropout rates. The focus of this study is to improve understanding of how students' perceptions of the online learning environment and student motivation from course design predict student drop out. This understanding will benefit faculty and institutions on student support for online developmental mathematics students.

The study included 330 undergraduate students enrolled in online developmental mathematics courses during the Fall 2018 semester at eight public universities and colleges in the Utah State Higher Education (USHE) system. Participants completed a survey with questions measuring their perceptions of the learning environment. They also completed a survey to measure student motivations toward their online mathematics coursework. Participants' answers were tied to data measuring course persistence, completion, and retention. The researcher used statistical analysis methods to generate findings.

The time-to-completion and regression analysis showed two things. The degree to which a student perceives that he or she can succeed at the coursework (self-efficacy) predicted student course persistence and completion in online developmental mathematics. Also, the ability of participants to identify with the online community (social presence) predicted student course persistence and

completion in online developmental mathematics. The analysis on student retention did not show any significant results.

This finding suggests that efforts and interventions geared towards building student self-efficacy and designing more social presence interactions may have the potential to increase course completion rates in online developmental mathematics coursework. Building self-efficacy in online developmental mathematics coursework, and a positive support group of fellow classmates through social presence, has the potential to give students the tools necessary to successfully navigate their own learning.

DEDICATION

This dissertation is dedicated to my wife, Jessie, who has been my rock and the main source of support, encouragement, and motivation throughout my doctoral studies. Her selflessness and serving attitude have lifted me through the challenging and difficult times. I am so much better for my association with her and she is my soul mate who makes my life complete. I will forever be grateful that she has chosen to walk this life with me. Secondly, I dedicate this work to my children who have demonstrated enormous amounts of patience and love to their father, even while he was often busy working throughout weekends and vacations. Lastly, I dedicate this dissertation to my parents and siblings who have provided a listening ear, thoughtful advice, and wise counsel.

This dissertation is a testament to the amazing group of people that love and support me.

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CHAPTER 1

INTRODUCTION

A college education represents future investment and opportunities. In 2016, the Condition of Education Report (McFarland et al., 2017) found that workers with a bachelor's degree or more advanced degrees had higher employment rates and salaries when compared to those with some college or only a high school degree. Many students seeking greater opportunities through the acquisition of an undergraduate degree need flexibility of time and location in coursework to earn a degree, and this makes them gravitate towards online learning (Jaggars, 2014). In 2016 about 5.8 million students in the United States took at least one online course. This follows a growth trend for the past 13 years, with more than a quarter of higher education students (28%) enrolled in at least one online course (Allen & Seaman, 2016). Online learning provides an opportunity for some students to obtain a university degree that they could not otherwise achieve.

Unfortunately, many students are not prepared to begin college level mathematics courses, as nearly 25% of students reported taking developmental mathematics classes (Sparks & Malkus, 2013). Scott-Clayton and Rodriguez (2015) found that, in community colleges, more than 50% of students are placed into a developmental mathematics course. Studies also show a large population that did not enroll in any mathematics course after their placement to a developmental mathematics course (Bailey, Jeong, & Cho, 2010). This implies that some students are likely to postpone the taking of developmental mathematics courses until a future semester. It is possible this delay might be attributed to the lack of course section availability needs that correspond to their personal and work schedule. In addition, students' personal and professional responsibilities can make taking courses in the traditional face-to-face format, meeting with the instructor and other students in the course at the same time and in the same location, a challenge (Jaggars, 2014). Therefore, a common instructional alternative is online learning. There then exists a current need to provide quality online instruction for students to improve their future opportunities.

Background of the Problem

Mathematics is an obstacle for many students seeking a college education (Bailey et al., 2010; Roksa, Jenkins, Jaggars, Zeidenberg, & Cho, 2009; Wang, Wang, Wickersham, Sun, & Chan, 2017). Students who complete their recommended developmental program are more likely to complete a four-year degree (Bettinger & Long, 2009). However, Bailey et al. (2010) found that fewer than half of the students referred to developmental coursework will actually complete the entire sequence. Not all this failure is attributed to student performance. One sample in the Achieving the Dream Initiative found about 21% of students recommended for placement in developmental mathematics had not enrolled in a developmental mathematics course within three years of initial registration (Bailey, 2009). Additionally, Bailey et al. (2010) found that men, older students, African American students, part-time students and students in vocational programs were less likely to complete their developmental course sequences.

The challenges of student course persistence and retention are only exacerbated when instruction moves to the online modality. As online instruction has grown in popularity, there have also been some growing pains with the delivery modality. Past research has shown retention issues in online education (Allen & Seaman, 2013). In 2007, 62% of higher education administrators said retention was an important or very important barrier to online education growth and in 2012 the number grew to 68.5% (Allen & Seaman, 2013). Online developmental mathematics instruction is not immune to this issue (Ashby, Sadera, & McNary, 2011). Students' persistence through an online course and retention within a program towards graduation are important for students to fulfill their goals. Providing high quality online instruction in developmental mathematics that supports students in these goals can improve their overall educational experience.

Statement of the Problem

In the United States, a liberal university education includes general coursework in mathematics. However, not all students are prepared for the rigor and difficulties that come with learning college level mathematics. Learning mathematics can be a struggle for many students in higher education (Roksa et al., 2009). This is partly due to gaps and holes in the students' prior knowledge and skills. One common solution is to provide students with developmental mathematics coursework (Bailey et al., 2010; Wang et al., 2017). However, students tend to drop out of developmental coursework, which can have lasting consequences on completing a college degree (e.g., Attewell, Lavin, Domina, & Levey, 2006; Bailey, 2009). Efforts to help students succeed in developmental mathematics are being explored at most institutions of higher education. The learning environment and student motivation are some factors which have been qualitatively identified by student perceptions to help with successful learning in developmental mathematics (Howard & Whitaker, 2011). However, the relationship of the online learning environment and student motivation towards course persistence and retention in developmental mathematics should also be explored. Effective online developmental mathematics instruction, that helps students persist through needed coursework and retains students at the university, is essential in the current educational environment.

Purpose of the Study

The purpose of this study was to examine how student perceptions of the online learning environment and student motivation predicted course persistence, course completion, and mathematics retention in developmental mathematics courses.

Significance of the Study

A high number of students are not prepared for post-secondary mathematics courses. Typically, these students are assigned to a developmental mathematics course. At times, due to personal or situational needs, students can only take their developmental mathematics course in the online modality. Instructional designers may learn better ways to design quality online developmental mathematics courses by understanding the students' perceptions of the learning environment and motivational factors. By examining these perceptions, faculty can design more effective online instruction to improve student persistence and retention rates in their online developmental mathematics courses.

A review of the research literature demonstrates the value of motivation and the learning environment on student learning (e.g., Broadbent & Poon, 2015; Kuo, Walker, Schroder, & Belland, 2014; Lee & Choi, 2011). However, there is limited research on the relationships among personal and academic factors with course persistence and retention in online developmental mathematics courses. This study focused on factors instructors can affect through course design and facilitation: the online learning environment and student motivation. The implications of this study provide guidance to instructors on the design elements that are most important for supporting course persistence and retention in online developmental mathematics courses.

Research Questions

This study answered the following overarching research question: How do students' perceptions of the instructor developed online learning environment, and their motivations derived from course design, predict course persistence, completion, and retention in online developmental mathematics courses? To answer this overarching question, three main research questions guided this study:

(1) How does the online learning environment and student motivation predict student course persistence?

(2) How does the online learning environment and student motivation predict student course completion?

(3) How does the online learning environment and student motivation predict student mathematics retention?

Overview of the Research Design

The research design for this study was a quantitative, non-experimental, cross-sectional survey design (Creswell, 2014). The researcher administered a survey to identified students enrolled in an online developmental mathematics courses using the Qualtrics platform to collect student perceptions of online learning environment factors and motivational factors in the Fall 2018 semester. Fall 2018 completion data and Spring 2019 enrollment data from participating students were collected from each institution. Perception data and institutional data were combined into one data set for analysis. The data analysis was performed in R and included multilevel survival analysis (RQ#1), multilevel logistic regression (RQ#2), and multilevel logistic regression (RQ#3).

Definition of Terms

The following key terms are defined for this study:

Developmental mathematics: Developmental mathematics education (also referred to as remedial mathematics or college remediation) describes precollege-level mathematics courses provided by postsecondary institutions to help academically underprepared students succeed in college-level mathematics courses (Higher Education Policy, 1998).

Online modality: A course where the instructor delivers over 80% (Allen & Seaman, 2016) of the "content, instruction, and materials over the Internet and the student attends class within this online classroom" (Robinson, Phillips, Sheffield, & Moore, 2015, p. 58).

Course persistence: The student's "ability to complete an online course despite obstacles or adverse circumstances" that may occur (Hart, 2012, p. 30). This is demonstrated by successful completion of the online course.

Attrition: The "opposite of course persistence" and results in the student's "withdrawal from an online course" (Hart, 2012, p. 30).

Retention: According to Hagedorn (2005), The National Center for Education Statistics differentiates the terms "retention as an institutional measure and persistence as a student measure" (p. 6). In this study, students who successfully complete the course and enroll in the next available mathematics course will be determined as retained. While student retention ultimately results in a completed degree, the time required to measure this is beyond the scope of this study.

Online learning environment: "A learning environment with no physical location and in which the instructors and students are separated by space" (Moore, 2016, p. 425). For this study, the online learning environment is defined as the instructor developed online learning environment, provided in the Community of Inquiry (Anderson, Rourke, Garrison, & Archer, 2001; Garrison, 2009; Garrison, Anderson, & Archer, 2001). The online learning environment is a combination of three presences: teaching presence, social presence, and cognitive presence.

Teaching Presence: "The design, facilitation, and direction of cognitive and social processes for the purpose of realizing personally meaningful and educationally worthwhile learning outcomes" (Anderson et al., 2001, p. 5).

Social Presence: "The ability of participants to identify with the community (e.g., course of study), communicate purposefully in a trusting environment, and develop inter-personal relationships by way of projecting their individual personalities" (Garrison, 2009, p. 352).

Cognitive Presence: "The extent to which learners are able to construct and confirm meaning through sustained reflection and discourse" (Garrison et al., 2001, p. 5).

Student Motivation: A "process that is inferred from actions and verbalizations whereby goal-directed physical or mental activity is instigated and sustained" (Jones, 2009, p. 272). For this study, student motivation was represented by the MUSIC® Model of Motivation.

Student Perception of Online Developmental Mathematics: Personal interpretation of the activities, events, and distribution of developmental mathematics course material in the online developmental mathematics course. This information is used to determine students' view of the online learning environment

(Garrison et al., 2001), and what motivations students develop from the course design (Jones, 2009).

CHAPTER 2

LITERATURE REVIEW

The purpose of this study was to examine how student perceptions of the online learning environment and student motivation predicted course persistence, course completion, and mathematics retention in developmental mathematics courses. By understanding the instructor-developed online learning environment and student motivational factors in online developmental mathematics courses, instructional and curriculum designers are better positioned to develop quality online instruction that promotes student persistence and course completion in online developmental mathematics courses.

This chapter discusses the previous research and literature for this study and is divided into six sections. The first section of this chapter looks at research and literature in online developmental mathematics for higher education. The second section of the chapter explores student persistence in coursework at institutions of higher education. The third, fourth, and fifth sections review the literature on retention, motivation, and the course learning environment. The final section of the chapter presents the conceptual framework for this study and the underlying theories of the framework.

Online Developmental Mathematics

The demand for online instruction in higher education has grown dramatically in recent years and the trends over the past 13 years indicate continual growth (Allen & Seaman, 2016). First, this section examines research on developmental mathematics. Second, this section explores the research on students' needs in developmental mathematics. Finally, this section examines the research in the online modality of developmental mathematics.

Developmental Mathematics Placement

Research shows that more than 50% of students entering a community college or university are placed into developmental coursework (Scott-Clayton & Rodriguez, 2015). Students are placed into developmental mathematics courses after taking a placement test that measures students' skill level in mathematics. Ultimate placement can be a result of poor test taking, long absences from a mathematics course, or even just a general lack of mathematical skill (Ngo & Kwon, 2015). Much of the research into developmental mathematics is focused on the effectiveness of initial placement on successful completion (Hughes & Scott-Clayton, 2011). Efforts are constantly being made to better place students into appropriate course levels to better provide the necessary learning (e.g., Bailey et al., 2010; Hughes & Scott-Clayton, 2011; Roksa et al., 2009; Scott-Clayton & Rodriguez, 2015).

Scott-Clayton and Rodriguez (2015) found they could not rely on a college placement tests as effective means to measure student learning in their study. The reason was because of the high rates of student dropout and retention issues, as students would not make it far enough in the study to take the posttest to compare with the pretest. This lack of tenacity, or persistence, to complete developmental mathematics coursework suggests two areas of further research: (1) Which factors support course persistence and retention in the online modality, and (2) Which of those factors are controllable by the developmental mathematics instructor? Supporting efforts to improve student course persistence and retention is important, as research has shown developmental mathematics to be one of the highest dropout areas of higher education (Bailey, 2009; Shulock et al., 2010). This study analyzed the effects of course design in online developmental mathematics courses on course persistence and retention in two areas where educators have some control: the learning environment and student motivation.

Educational Availability of Developmental Mathematics

While this study was not focused on traditional vs nontraditional populations, studies show that online education attracts a higher nontraditional student population (Wladis, Hachey, & Conway, 2015). The societal demands on students are much different than they were when higher education was first created (Marginson, 2016). Online education provides opportunities for student populations that would not otherwise be able to achieve educational goals. With the increase of online educational opportunities, also comes the demand to provide quantity to meet the needs of this growing population (Jaggars, 2014). Many nontraditional students have not had formal mathematics instruction or practice for many years. This lack of mathematics instruction and practice is one reason why colleges and universities need to provide developmental mathematics course offerings to students (Hughes & Scott-Clayton, 2011). In 2011, the National Center for Education Statistics reported that 38% of students are over the age of 25 with this number projected to increase another 23% by 2019 (Snyder, 2015).

In general, main reasons students sign up for online coursework are flexibility of the schedule, convenience, effectiveness of online classes, and the fit with their educational goals and efforts (Willging & Johnson, 2009; Wladis et al., 2015). Online education provides opportunities for students that would not have the possibility of an education otherwise (Wladis et al., 2015). This study focused on which factors of the course learning environment and motivation are related to student course persistence and retention. This information can aid online instructors and instructional designers to improve the quality of online developmental mathematics courses and address the growing needs of nontraditional students.

Online Delivery of Developmental Mathematics

Distance education helps address student needs when they cannot attend classes at a certain location or at a certain time. The most popular form of distance education in the 21st century is online instruction (Simonson, Smaldino, & Zvacek, 2014). Online learning has dramatically grown over the past decades as Internet technologies have increased and made distance learning more accessible than ever before (Simonson et al., 2014). This growth is due to increasing technology development and access. Also, increased student enrollments of online undergraduate courses demonstrate the growth of online education. In 2014 about 25% of undergraduate students participated in some form of distance learning in the US, with online education containing the greatest percentage of those students (Kena et al., 2016).

In 2014, of the 5.8 million students taking online courses, 2.85 million students take online courses exclusively and 67% of all distance education students are in the public sector (Allen & Seaman, 2016). This is of interest as online education was mostly in the private sector when it was first developed. Now, two-thirds of academic leaders mention online education as being important to the long-term strategy at their universities (Allen & Seaman, 2016). The growth of different delivery options is becoming more popular in higher education institutions with students taking courses in face-to-face, online or blended modalities.

As online learning continues to grow, more research needs to be conducted to support quality instruction. Since students have flexible needs when it comes to course delivery, coursework in developmental mathematics needs to be part of offerings for institutions who choose online delivery. This study focused on online coursework to provide deeper understanding of the quality provided in online developmental mathematics coursework.

Comparing Face-to-Face Learning with Online Learning

Much of the research with online coursework has looked at the learning outcomes of face-to-face courses vs online courses to see if student learning outcomes are equivalent. Ashby et al. (2011) found that online students performed worse than face-to-face students. However, when the analysis controlled for attrition, the face-to-face students on average, performed worse. Ashby et al. (2011) concluded that one cannot look at research in online education without taking attrition into consideration. This study aimed to address the concerns of online course persistence.

Skepticism over the quality of online education has decreased as research has demonstrated that students can meet the same learning outcomes independent of the delivery method. Over half of the academic leaders of higher education say that online and face-to-face outcomes and measures are the same, with 17% calling online outcomes superior to face-to-face (Allen & Seaman, 2016). Part of the increases in the acceptance of online learning is due to technological improvements which allow for more robust online learning environments. The online learning environment does not refer to an automated instruction, computer self-pacing, or independent study. The best online learning environment involves a teacher creating a virtual learning environment, facilitating the learning, guiding students through the curriculum, and offering feedback.

Many studies in the literature focus on comparing face-to-face with online (e.g., Ashby et al., 2011; Hostetter & Busch, 2006; Pigliapoco & Bogliolo, 2008;

Starling, 2011; Trenholm, 2009). However, future research should not solely compare face-to-face learning with online learning. Research should include the comparison of online courses with other online courses to define, understand, and improve the quality of instruction in online learning for developmental mathematics.

One important finding is that online education seems to promote a change in administrator and faculty roles (Mitchell, 2009). Some institutions have begun using the term “facilitator” to replace that of “instructor” and “teacher” in job descriptions and contracts for online instructors (Mitchell, 2009). These changing definitions of roles are moving into the face-to-face instruction as comments such as “teachers are guides on the side and not sages on the stage” are becoming much more popular among faculty at post-secondary institutions (Morrison, 2014).

This study addressed questions regarding student perceptions of the online learning environment with course persistence and retention in developmental mathematics. The need for online developmental mathematics will only increase in the future. Instead of comparing different modalities, researchers need to change tactics and approaches to begin improving the quality of online instruction.

Student Persistence and Retention

Dropout rates in online classes are higher, in general, when compared with face-to-face instruction (Ashby et al., 2011; Lee & Choi, 2011; Zavarella & Ignash, 2009), and developmental mathematics is no exception. Zavarella and Ignash (2009) found that students in online classes had a dropout rate higher (39%) than face-to-face students (20%). The researchers made an effort to contact the students who withdrew (n = 64) and 11 out of the 20 who withdrew from the online section mentioned that “the course presented challenges they did not anticipate” (Zavarella

& Ignash, 2009, p. 6). Zavarella and Ignash (2009) hypothesized students may have perceived the computer-based instruction to be less challenging than that of a traditional lecture-based course or possibly less time-consuming.

Additional studies indicate that almost 60% of students enrolled in community colleges take at least one developmental mathematics course with around 30% of those students finishing the developmental mathematics course sequence (Attewell et al., 2006; Bailey, 2009; Trenholm, 2009). One comparative study found that while 93% of students completed a face-to-face course, only 76% completed the online course and 70% completed the blended course, which contains both face-to-face and online components (Ashby et al., 2011). The researchers suggested that future research should look into retention issues caused with the online and blended courses (Ashby et al., 2011).

Online courses, in general, seem to have lower pass rates (Ashby et al., 2011). This issue is not isolated just in developmental mathematics as other studies also confirm higher attrition rates in online courses (Patterson & McFadden, 2009; Xu & Jaggars, 2013). This study aimed to add understanding to the higher attrition rates in online developmental mathematics.

Lee and Choi (2011) identify one major concern in the ambiguity in reporting attrition rates because of the variety of semester duration and different interpretations. The researchers (Lee & Choi, 2011) found some articles define dropout as non-completion of the course while other studies considered students who withdrew or received a failing grade as dropouts. In another study, the researchers defined dropouts as those who failed to enroll in the subsequent year (Pigliapoco & Bogliolo, 2008). With the ambiguity that exists in the different definitions, Coleman, Skidmore, and Martirosyan (2017) suggest that researchers should critically interpret literature when looking at online developmental mathematics courses to avoid confusion. Therefore, this study defined both course persistence as a time-event outcome factor and retention as successful enrollment in a mathematics course for the subsequent semester.

In reviewing literature of online course dropouts, Lee and Choi (2011) found 69 factors that contributed to online student dropout rates. Most of these factors were self-reported by students and the researchers classified the factors into three categories: Student Factors, Course/Program Factors, and Environment Factors (Lee & Choi, 2011). Other researchers classified the factors as Personal Variables, Institutional Variables, and Circumstantial Variables (Berge & Huang, 2004). This speaks to the complexity in creating a complete picture of student course persistence and retention when studying online learning.

A wide range of variables affect student course persistence and retention. The researcher focused this study on the online developmental mathematics learning environment and student motivation. In particular, the study examined how the course design of the online learning environment motivated students. This information contributes to a better understanding of how course designers and instructors can promote students' persistence in online developmental mathematics courses.

Online Learning Environment

There are many ways to define the online learning environment. To best understand the framework for this study, it is important to understand what a learning environment looks like in a traditional, face-to-face setting. Instructors create a physical setting, typically in a classroom, which creates the environment where students can learn. However, a learning environment is more than just a room with a chalkboard and rows of desks. It is "the diverse physical locations, contexts, and cultures in which students learn" (Education Reform, 2013).

Online learning environments are more than just the Learning Management System (LMS), just as the face-to-face learning environment is more than the classroom. The online learning environment includes the context and culture for how students learn. One particular model, Community of Inquiry (CoI) identifies the learning environment as a combination of teaching presence, social presence, and cognitive presence (Arbaugh et al., 2008).

The teaching presence has the potential to increase student retention. Lee and Choi (2011) identified faculty interaction with students and extensive faculty feedback as some of the course/program factors that had a positive effect on decreasing dropout rates. While students are attracted to online courses for the flexibility and convenience, they are also pushed away when there is a weaker teaching presence and fewer student-student interactions (Jaggars, 2014).

Jaggars (2014) found in the interviews with 46 respondents that 40% of the respondents mentioned they would never take a mathematics course online. The isolation that students might feel in the online environment plays a major role in their decision to persist or dropout. A student's perception of the presence and support of an instructor can greatly affect the determination and drive to persist through a course (Lee & Choi, 2011).

In one study, Bonet and Walters (2016) discovered how instructor presence resulted in higher levels of student-faculty engagement. While the study focused on face-to-face instruction, the researchers found that the more students perceived the presence of the instructor, the more they attended class and were active in their required activities, which increased course persistence. Similarly, researchers conducting a meta-analysis on face-to-face courses (Cornelius-White, 2007) found that learner-centered teacher-student relationships had a high correlation in participation, student satisfaction, dropout prevention, self-efficacy/mental health, positive motivation, and social connection/skills. These examples of teaching presence exemplify the need for further research on the relationships and effects of teaching presence on course persistence and retention in the online environment.

Studies have shown that social presence plays an integral part in successful online courses (Carr, 2014; Garrison, Cleveland-Innes, & Fung, 2010). Carr (2014) suggests that social presence in an online course can be enhanced by providing opportunities for student-to-instructor and student-to-student interactions. One concern is that the concept of social presence in an online environment is rather new and researchers do not necessarily have a common definition or measure (Lowenthal, 2009). The importance of looking at social presence as a predictor of retention can indicate the importance of encouraging and building a learning environment in which students encourage and support one another. Oseguera and Rhee (2009) found students who feel isolated from other students or lacked a sense of belonging were more likely to leave an institution.

This sense of belonging or sense of community that students feel is no less important in the online environment than it is in a face-to-face environment. Literature shows that there is a connection between student interaction and a sense of community or belonging, including in online environments (Delahunty, Verenikina, & Jones, 2014). As students communicate and interact more there is an increased sense of belonging, which can be a predictor of student persistence in STEM, especially more so with underrepresented groups such as women (Lewis et al., 2017). Social presence in a virtual environment has the potential to increase students' feeling of acceptance and belonging, which helps with persistence.

In another study, Boston et al. (2009) looked at 28,877 students over six semesters studying at a for-profit online university who completed the CoI survey. The focus population was military students, with 68% male participants and 32% female participants. The mean age of the sample was 28.2 years old, reflecting quite a few nontraditional students at this institution. The findings showed two indicators played a role on retention: (1) *online or web-based communication is an excellent medium for social interaction;* (2) *I was able to form distinct impressions of some course participants.* These results indicate that social presence within an online course plays a role in student retention and may also contribute to retention for students in online developmental mathematics.

Research is limited on the effect the cognitive presence has on retention and has been explored more as an outcome variable. For example, Shea and Bidjerano (2009) found an equation modeling 70% of the variance in measuring the cognitive presence based upon the social and teaching presences. Studies have found if the course material is too challenging it can affect retention and course persistence (Jaggars, 2014; Poellhuber, Chomienne, & Karsenti, 2008). In developmental mathematics, these findings would encourage the use of placement exams to make sure a student is placed in the proper level of mathematics, so they can process the information properly.

This study encouraged the analysis of the effect the perceived online learning environment has on course persistence and retention in developmental mathematics. In particular, this study analyzed how long students persist in a course based on the different learning environment variables. Much of the literature reviewed of the online learning environment was generalized to all online education with a few available mathematical studies. There is a gap in the literature on the relationships and effects of the learning environment in online developmental mathematics courses.

Motivational Factors: Student Satisfaction and Sense of Community

Aspects of the learning environment (such as social presence) have a connection to student satisfaction (Hostetter & Busch, 2006) and sense of community (Guilar & Loring, 2008), which are both motivational factors. Xu and Jaggars (2013) found that students with poorer preparation and lower motivation are more likely to struggle in online courses. There are many other factors of motivation (e.g., locus of control, self-efficacy, task value, attributional theory of achievement, etc.). Many studies have looked at these different predictors to show the effects of motivation on retention (Joo, Lim, & Kim, 2013). Motivation is a very complex construct with a variety of factors and isolating which factors play an important role in course persistence and retention is difficult. Lee and Choi (2011) identified 69 dropout factors categorized into three groups of student factors, course/program factors, and environment factors. Twenty percent of the factors in the meta-analysis were focused on psychological attributes or the students' attitudes towards learning in general with several studies indicating a significant correlation between students' motivation and successful completion of individual online courses and programs Lee and Choi (2011). Motivation was measured by questions about students' attitudes toward learning goals, homework, and interaction with peers. Lee and Choi (2011) further cited Chyung (2001)'s study that examined the impact of instructional design model to improve students' academic performance and course dropout rate in master level courses. With a wide range of variables, the researcher concentrates on specific research-based motivational factors related to course design to limit the focus of the study.

Instruction in developmental mathematics courses suggests students have taken classes covering similar content and have been unsuccessful in retaining the information. These previous struggles tend to reduce motivation and self-efficacy (Boaler, 2016; Simzar, Martinez, Rutherford, Domina, & Conley, 2015).

The more motivated a student is, the more likely the student will be engaged with the course materials. Curricular engagement is widely recognized as crucial for learning and retention (Trowler & Trowler, 2010). Kahu and Nelson (2018) suggest a model of engaged learning that include areas of motivation, which can be affected by university policies and curricular choices. Schunk, Pintrich, and Meece (2008) explained that motivation consists of actions and verbalizations that lead to goal-directed activities. The decision to persist or dropout of a course is one such goal-directed activity.

The researcher focuses on a particular framework of motivation for direction and purpose due to the wide range of motivational purposes and factors. Jones (2009) developed the MUSIC® Model of Motivation, which focuses on five motivational factors (eMpowerment, Usefulness, Success, Interest and Caring). This model is explained in more detail in the conceptual framework below. The MUSIC model is a motivational and instructional model designed to improve student success in higher education courses. Snyder (2015) used this model to research at-risk populations and found that three of the factors (usefulness, success and care) had the potential to improve academic achievement with at-risk high school students.

While the MUSIC model has been used in many courses, it has not been yet researched in developmental mathematics courses. Even with engaged and motivated students, mathematical motivation appears to be a separate attribute than academic motivation (Guy, Cornick, & Beckford, 2015). There is a lack of research to better understand how mathematics curriculum design affects student engagement and retention. This study aimed to fill this gap in the literature on how student perceptions of the course generate motivation and furthermore promote course persistence and retention. The researcher also analyzed the correlational effects of the online learning environment factors with motivational factors.

Conceptual Framework

In this section, the researcher introduces the conceptual framework for this study. First, this section discusses two types of retention models with the holistic model approach ultimately being selected. Second, the theoretical framework of the Social Cognitive Theory with the Triadic Reciprocal Causation is discussed, along with how it relates to the conceptual framework. Third, the researcher introduces a new conceptual framework based off the Curriculum and Instruction area in the Berge and Huang (2004) model. Lastly, the researcher introduces the final conceptual framework by adding the online learning environment factors from the Community of Inquiry and the motivational factors from the MUSIC model into the final model.

Retention in Higher Education

Research shows the importance of retention in higher education (e.g., Bailey et al., 2010; Demetriou & Schmitz-Sciborski, 2011; Ngo & Kosiewicz, 2017). In the 2016 *Digest of Education Statistics*, the National Center for Education Statistics stated that of the 1.7 million first-time, full-time, degree-seeking students who began school in 2009, only 39.8% earned a degree in four years and 59.4% completed their degree within six years (U.S. Department of Education, 2016).

It is estimated that over the past 20 years, more than 31 million students have enrolled in college and left without receiving a degree or certificate (Clearinghouse, 2014). Because of the importance of retention, research over the past 40 years has tried to understand more about the effects and predictive factors on students' decisions to dropout or persist (Lee & Choi, 2011). Some of these factors include academic preparation, academic engagement, social engagement, financing college, and demographic characteristics (Demetriou & Schmitz-Sciborski, 2011). The variety of factors demonstrates the complexity of understanding the reasons behind a student's decision to persist or dropout. While many of these factors can be controlled by institutions of higher education, other factors remain beyond the control of an institution.

Two Types of Retention Models

In the literature there are two major types of retention models: path models and holistic models. Most path retention models stem from Tinto (1975)'s Longitudinal Model of Individual Departure. Path models are graphically represented in a flowchart-like manner. Tinto (1975)'s work on student integration has long been used and adopted to explain student departure. Many researchers looking at retention in distance education developed path retention models from his work (e.g., Kember & Gow, 1989; Rovai, 2003).

The second type of retention model is the holistic model. While path models offer deep understanding of the variables behind a student's decision to persist or dropout, the researcher's questions better align with a holistic model approach. In the Sustainable Retention Model suggested by Berge and Huang (2004), the researchers take on a more holistic approach (see Figure 2.1). These researchers theorize in their model that the decision to persist or drop is a combination of personal variables, institutional variables and circumstantial variables with decisions based upon delivery modality and focused on institution-controlled factors such as Curriculum & Instruction, Academic & Social Supports, and Institutional Management. Isolating each of these variables is impossible as decision making processes are a combination of many different variables made by each individual student (Berge & Huang, 2004).

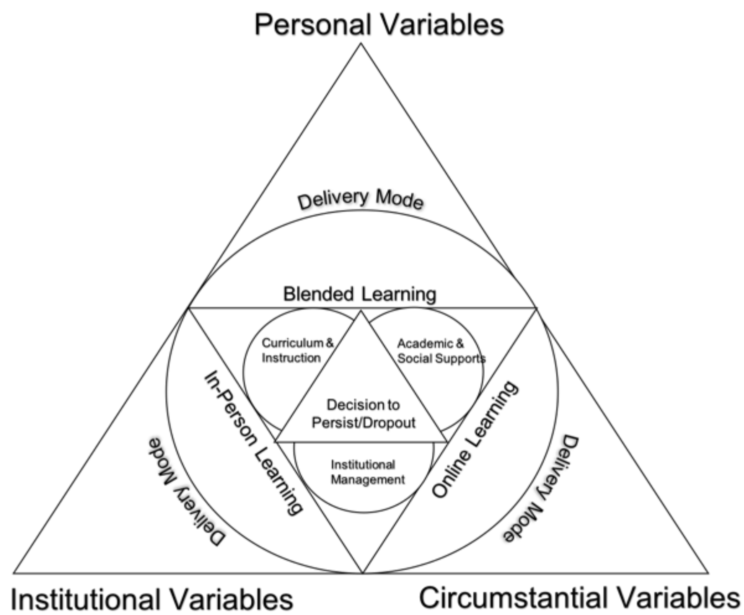

Figure 2.1. Sustainable Retention Model by Berge and Huang (2004).

The focus of this study was to further analyze and understand the variables located under the Curriculum and Instruction area of the Berge and Huang (2004) model. While there are many other factors that ultimately play a role in the decision to persist or dropout of a course, isolating this study's focus helped in defining and creating a measurement of retention as it pertains to course design and the pedagogical instruction.

Theoretical Foundation

Bandura (1986) argued a person's behavior, personal factors (e.g., cognition, affect and biological events), and environmental factors are mutually interacting. Bandura developed the Triadic Reciprocal Causation model to explain how each construct is an interacting determinant upon the other two constructs (see Figure 2.2).

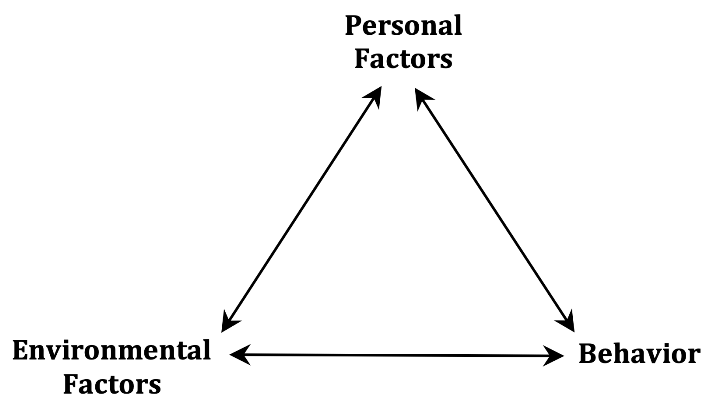

Figure 2.2. Bandura's (1986) Triadic Reciprocal Causation.

Conceptual Framework

The conceptual framework for this study applied Bandura (1986)'s Triadic Reciprocal Causation Model. The behavior considered in this interaction is the student's decision to persist/dropout of a course and retain their enrollment in mathematics education. The personal factors in this interaction are the perceptions of how the online developmental mathematics course motivates the student. The environmental factors in this interaction are the perceptions of the online learning environment of a developmental mathematics course. Figure 2.3 demonstrates this modification.

Learning environment factors. The Community of Inquiry (CoI) (Garrison, Anderson, & Archer, 2000) framework is frequently used when

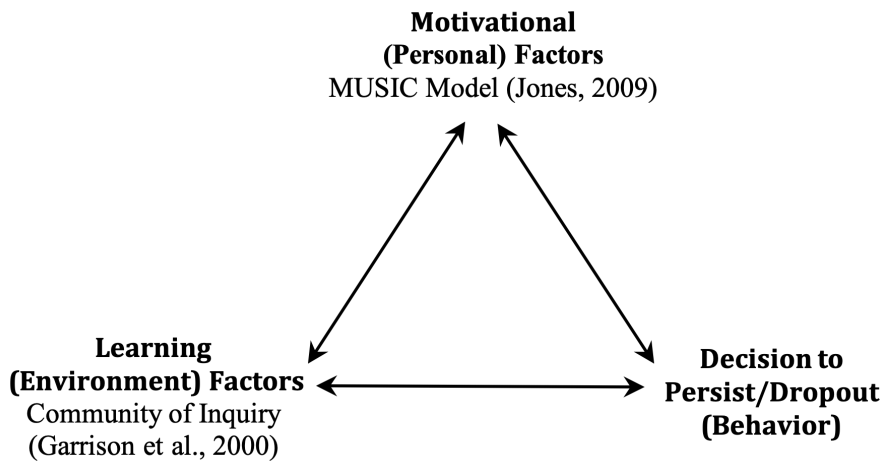

Figure 2.3. Curriculum and Instruction Effect on Course Completion Model.

researching online learning environments in general (e.g., Arbaugh, 2007; Swan et al., 2008). However, the CoI (Garrison et al., 2000) has not extensively been used to examine mathematics or developmental mathematics courses and there is an opportunity to expand the research literature with this model. Garrison et al. (2000) suggest that an ideal online learning environment should contain three core elements: cognitive presence, social presence, and teaching presence. These three factors were used to define and analyze the online learning environment in this study.

Motivational factors. As explored previously in this chapter, many motivational factors play a role in student course persistence and retention (e.g. self-efficacy, attributional theory of achievement, self-determination, etc.). In the MUSIC model, Jones (2009) measures the level of increased student learning in course design by looking at five factors: eMpowerment, Usefulness, Success, Interest, and Caring (see Table 2.1). By measuring these five factors, instructors and course designers can identify the level of student motivation and isolate areas of needed improvement. This study investigated the five factors of the MUSIC model to measure their relationship with students' course persistence and retention.

Table 2.1

The MUSIC Model of Academic Motivation Inventory Constructs and Their Definitions

MUSIC model constructs	Definitions The degree to which a student perceives that:	Related constructs
eMpowerment	he or she has control of his or her learning environment in the course	Autonomy (Deci & Ryan, 1991)
Usefulness	the coursework is useful to his or her future	Utility value (Wigfield & Eccles, 2000)
Success	he or she can succeed at the coursework	Expectancy for success (Wigfield & Eccles, 2000)
Interest	the instructional methods and coursework are interesting	Situational interest (Hidi & Renninger, 2006)
Caring	the instructor cares about whether the student succeeds in the coursework and cares about the student's well-being	Caring (Noddings, 1992)

Note. From the "User Guide for Assessing the Components of the MUSIC Model of Motivation", by B. D. Jones, 2017, p. 5, available at www.theMUSICmodel.com. Copyright 2017 by Brett D. Jones.

Final conceptual framework graphic. The researcher started with the Berge and Huang (2004) Sustainable Retention Model (see Figure 2.1) and focused on the Curriculum and Instruction piece which was the top left semicircle in the middle of the model. Next, applying the Curriculum and Instruction Effect on Course Completion Model (see Figure 2.3) the researcher inserted the interaction to be studied into the Curriculum and Instruction area. This final conceptual framework is demonstrated in Figure 2.4.

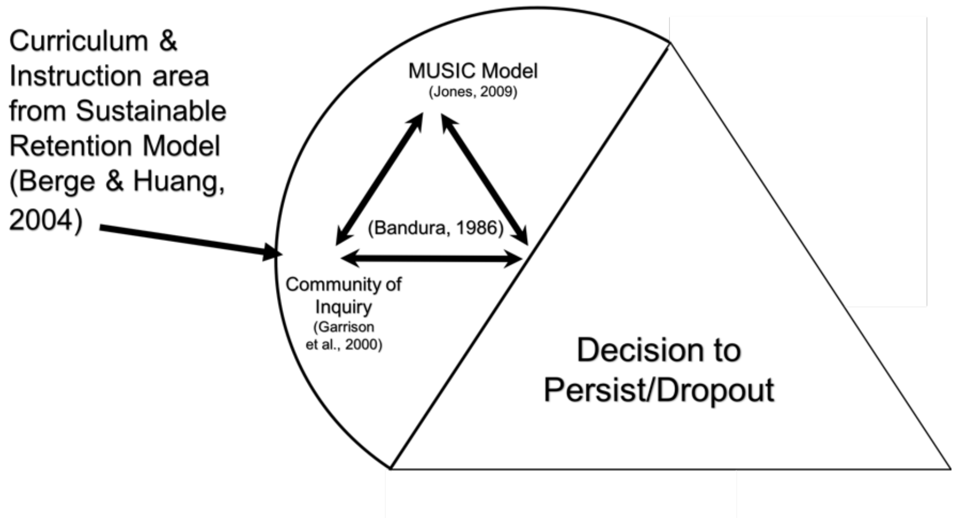

Figure 2.4. Curriculum and Instruction Effect on Course Completion Model within Sustainable Retention Model.

Summary

This chapter explores the research in student persistence and retention in online developmental mathematics courses. Research in the learning environment and student motivational factors were also examined to identify successful factors and models and connections to course persistence and retention. Further research should be conducted to analyze the relationships between the learning environment and student motivation in online developmental mathematics courses and students' persistence and retention rates. Lastly, this chapter introduces a conceptual framework developed from prior theoretical frameworks and evidence-based models to explore the relationships of motivation, learning environment, and students' behaviors. This conceptual framework is the basis of this study, which explores the associations of online developmental math, students' perceptions of the course learning environment, their perceptions of how the course motivates them, and their ultimate decisions to persist in an online developmental course and retain their enrollment in mathematics education.

CHAPTER 3

METHODS

The purpose of this study was to examine how student perceptions of the online learning environment and student motivation predicted course persistence, course completion, and mathematics retention in developmental mathematics courses. This chapter outlines the research design of the study, participants of this study, data sources used, data collection, data analysis, addresses ethical considerations, and discusses limitations to this study.

Research Design

The research design for this study was a quantitative, non-experimental, and cross-sectional survey design (Creswell, 2014). The purpose of this design was to generalize the perceived characteristics of the online learning environment and student motivation factors on course persistence and retention in online developmental mathematics students (Creswell, 2014; Lavrakas, 2008). The researcher analyzed survey data using preliminary analysis including descriptive statistics and correlations. Frailty multilevel survival analysis methods and multilevel logistic regression were used to analyze the research questions. This study added to previous studies on the importance of the online learning environment (Swan et al., 2008) and student motivation in course design and delivery (Jones, 2009, 2018). Table 3.1 provides a timeline overview of this study.

Participants and Sampling

Participants in this study were 330 undergraduate students enrolled in online developmental mathematics courses at eight public universities and colleges in the Utah State Higher Education (USHE) system. These institutions included: Dixie

Table 3.1

Timeline of Research Study Design

Phase Step	Phase Name	Tasks
Phase 1	Recruit Institutions	Emailed departments responsible for developmental mathematics and received letters of support.
Phase 2	Institutional Review Board (IRB) Approval	Received IRB approval of study from Utah State University and reach out to each participating institution's IRB office to fulfill requirements/requests.
Phase 3	Recruit Courses	Contacted instructors of online developmental mathematics courses and requested support.
Phase 4	Distribute Survey	Distributed survey to participants using Qualtrics and having instructors send unique course URL to students.
Phase 5	Collect Persistence & Retention Data	Requested course completion and retention data from each participating institution on study participants.
Phase 6	Complete Data Analysis	Completed data analysis to answer research questions.

State University, Salt Lake Community College, Snow College, Southern Utah University, University of Utah, Utah State University, Utah Valley University, and Weber State University. The researcher recruited participants, ages 18 and older, for this study from students in developmental mathematics courses, typically titled "Elementary Algebra," "Introductory Algebra," or "Intermediate Algebra," taught in the online modality. Identified courses for this study were not required for graduation, but participants were placed in these developmental courses to improve their mathematics skills and prepare them for degree-level mathematics. Therefore, all students in the study needed to take future mathematics courses upon successful completion of the developmental courses or retake the same course if they failed or withdrew from the course.

All courses were fully-online courses, which means they did not hold classes in the same physical location at the same time. However, to better interpret the data, the researcher asked the instructors no more than two questions to help clarify each course type (identified as ‘synchronous,’ ‘asynchronous,’ or ‘independent’). First, are students required to work together for any assignments, or is every assignment done independently? Second, if the answer is yes, are there any synchronous components in their online courses (e.g., students required to meet with each other at the same time)? If the answer was yes to both questions, the course type was considered ‘synchronous’. If the answer was yes to the first question and no to the second, the course type was considered ‘asynchronous’. If the answer to the first question was no, then the course type was considered ‘independent’.

Every instructor who replied indicated that there was no requirement for students to work together. While there were varying degrees of encouraging students to create study groups, Q&A discussions, or receive supplemental support (e.g., tutors), none of the courses in this study were designed to require student collaboration. Therefore, all courses in this study were defined as ‘independent’.

Table 3.2 provides a summary of the demographic information on the study participants. While these data were not needed or used in the analysis portion of this study, the demographic information provides a better understanding of the sample who provided the questionnaire responses.

Table 3.2

Demographics of Study Sample

Factor	Count	Percent
Age (n = 317)		
18 – 23	147	46.4%
24 – 30	90	28.4%
31 – 40	55	17.4%
41 – 50	19	6.0%
50+	6	1.9%
Gender (n = 320)		
Woman	221	69.1%
Man	95	29.7%
Nonbinary	2	0.6%
Unsure/undecided	2	0.6%
Years Since Last Math Class (n = 319)		
Less than a year	88	27.6%
1 – 2 years	74	23.2%
3 – 5 years	60	18.8%
6 – 10 years	49	15.4%
11 – 20 years	38	11.9%
21+ years	10	3.1%
Marital Status (n = 322)		
Married	128	39.8%
Partnered	32	9.9%
Single, never married	145	45.0%
Divorced / Widowed	17	5.3%
Have Dependents (n = 324)		
Yes	114	35.2%
No	210	64.8%
Financially Independent (n = 308)		
Yes	205	66.6%
No	103	33.4%
Earned High School Diploma (n = 326)		
HS Diploma	310	95.1%
GED	15	4.6%
None	1	0.3%

One particular result that helps demonstrate the divided time constraints that online students are undergoing is shown on Table 3.3. Over a quarter of the students in the study declared that they were both full-time students and working full-time (26%). Also, 25% of the students were part-time students while working full-time and 23% of the students were full-time students working part-time. This aligns with the literature that online education attracts a higher nontraditional student population (Wladis et al., 2015).

Table 3.3

Work and School Time Commitment from Study Sample

Factor	Work				
	Full-time	Part-time	Not Employed	Declined Answering	Total
Schooling					
Full-time	83	74	40		201
	(25.2%)	(22.4%)	(12.1%)		(60.9%)
Part-time	80	29	13		124
	(24.2%)	(8.8%)	(3.9%)		(37.6%)
Declined					5
Answering					(1.5%)
Total	164	103	53	10	330
	(49.7%)	(31.2%)	(16.1%)	(3.0%)	(100.0%)

Note. Percentages in parenthesis are calculated from total sample size.

Recruiting Procedures

The researcher contacted university departments at each participating institution responsible for the instruction of developmental mathematics courses and briefly explained the study and requested letters of support (see Appendix D). Next, the researcher obtained Institutional Research Board (IRB) approval through Utah State University for the study. Afterwards, the researcher reached out to each of the IRB offices of the participating universities and satisfied the unique requirements of each institution.

The researcher then reviewed public course enrollment information for the Fall 2018 semester and identified all course sections that satisfied the requirements of the study (i.e., online, developmental mathematics courses). There were 49 sections of online, developmental mathematics that met the criteria. The targeted recruitment population came from those 49 sections taught by 36 unique instructors with a population of 1,982 students as of August 24, 2018. The researcher contacted the head of each department responsible for developmental mathematics with information regarding the study and requested confirmation on the researchers work and permission to solicit instructors to include their online, developmental mathematics course sections in the study (see Appendix E).

The researcher sent recruitment emails to each identified instructor requesting the instructor's support in the study (see Appendix F). To collect survey data, the researcher combined surveys and demographic information on the same instrument to distribute to participating instructors through Qualtrics (see Appendix B). The researcher incentivized the study by providing participating institutions and instructors with the results and findings of the study. To increase response rates, the researcher provided a $5 Amazon gift card to all participants. Three instructors chose to offer credit or extra credit instead of the $5 gift card which IRB agreed was equivalent incentive.

There were 27 instructors, representing 34 out of the available 49 sections, who agreed to participate in the study and send the recruitment letter to their students. A total of 1,187 students received the recruitment email and/or announcement in their online course from their instructor which contained a unique survey link for their course section (see Appendix G). After 2 weeks of data collection, 317 participants had submitted a survey. The researcher decided to do a 48-hour blitz to try and get a few more participants and requested the instructors to send out one more recruitment email (see Appendix H). After the last recruitment, a total of 364 participants completed the survey.

Data Sources

There were two types of data collected in this study. These data were generated from (1) surveys and (2) institutional records.

Measures

The first source of data for this study was two surveys measuring students' perceptions of their learning environment and their perceived motivation in an online developmental mathematics course. The first survey, the Community of Inquiry Survey (Arbaugh et al., 2008), measures three factors (teaching presence, social presence, cognitive presence) of the course learning environment. The second survey, the MUSIC® Model of Academic Motivation Inventory (Jones, 2009, 2018) examines the five constructs found to motivate students in college courses (eMpowerment, Usefulness, Success, Interest and Caring). Both surveys were administered to participants at the same time to provide the cross-sectional participant perceptions of the online mathematics course and increase the reliability of the connections between the learning environment and motivation.

Community of Inquiry Survey. The Community of Inquiry Survey (COIS) (Arbaugh et al., 2008) contains 34 agreement Likert-scale items with 13 items measuring teaching presence, nine items measuring social presence and 12 items measuring cognitive presence. An example of an item measuring teaching presence is, "the instructor clearly communicated important course topics." An example of an item measuring social presence is, "getting to know other course participants gave me a sense of belonging in the course." An example of cognitive presence is, "learning activities helped me construct explanations/solutions." The researcher used all items from the COIS to develop the instrument for the study (see Appendix B).

In a study with 287 participants, Arbaugh et al. (2008) found that the survey had Cronbach alpha values of 0.94 for teaching presence, 0.91 for social presence and 0.95 for cognitive presence. As well, factor analysis resulted in 0.96 for a Keyser-Meyer-Olkin measure of sampling accuracy, thus indicating distinct and reliable factors.

MUSIC® Model of Academic Motivation Inventory. The MUSIC® Model of Academic Motivation Inventory measures college students' beliefs on five principles. These constructs are eMpowerment, Usefulness, Success, Interest and Caring (Jones, 2009, 2018). These constructs were designed to provide a framework to best determine how to design experiences for students to cognitively motivate them in their courses and can be used "to research relationships among factors critical to student motivation" (Jones & Skaggs, 2016, p. 3). An example of an item measuring eMpowerment is "I have the opportunity to decide for myself how to meet the course goals". An example of an item measuring Usefulness is "the coursework is beneficial to me." An example of an item measuring Success is "I am confident that I can succeed in the coursework." An example of an item measuring Interest is "I enjoy completing the coursework." An example of an item measuring Caring is "the instructor cares about how well I do in this course." All items from the MUSIC inventory are included in the survey (see Appendix B).

Jones and Skaggs (2016) reported in a study with 338 undergraduate students in 221 different courses Cronbach alpha values of 0.91 for eMpowerment, 0.96 for Usefulness, 0.93 for Success, 0.95 for Interest, and 0.93 for Caring. The instrument for this study uses all 26 items and the authors of the instrument gave permission to use the survey (see Appendix C).

Institutional Record Data

Powell, Conway, and Ross (1990) discussed the difficulty of the many variables and multivariate nature of retention models. Powell et al. (1990) stated that studies "have been hampered by the use of a limited range of measures and a lack of standardized measures, and the use of single items to measure broad concepts" (p. 23). To generate data for the dependent variables of student course persistence and retention, the researcher collected data from each institution's registrar's office. Student course persistence was determined by receiving student course completion status from the registrar's office of each participating institution. To perform the analysis properly, the researcher needed to receive the last date of attendance or academic activity as determined by the instructor on grades of Unofficial Withdrawal (UW). The researcher also requested from the registrar's office of each institution the successful student enrollment in the next mathematics course for the next consecutive semester. The researcher collected this information as a dichotomous variable in the yes/no form.

The last piece of institutional record data was a grade distribution for every online developmental mathematics course. This information was used to gather course completion data for the entire online developmental mathematics courses in the Fall 2018 to compare the sample data to the general population.

Procedures

Data Collection

Data collection was completed in two stages. In the first stage, the researcher collected survey data with student perceptions of the online learning environment and motivation in the third and fourth weeks of the semester following the recruitment procedures. At the beginning of the fifth week, the researcher decided to perform a 48-hour last call recruitment blitz to increase the sample size.

In the second stage, the researcher collected institutional record data from the registrar office at the beginning of the Spring 2019 semester. This was done to make sure grades were completed from the Fall 2018 semester and student enrollments for Spring 2019 were completed.

Survey data collection. The survey instrument contained: (1) 26 Likert-type questions, measuring motivation from the MUSIC model (Jones & Skaggs, 2016); (2) 34 Likert-type questions from the Community of Inquiry Survey, developed by Arbaugh et al. (2008) measuring the online learning environment, and; (3) demographic questions. The researcher prepared the instrument into six parts with 10 questions and part seven contained the demographics questions (see Appendix B).

The researcher worked with department chairs following the recruitment procedures outlined previously to inform instructors of the study and make sure they had all needed materials. At the beginning of the third week in the Fall 2018 semester, the researcher emailed a reminder to the instructors with instructions to share with students (see Appendix G). Another follow-up email to instructors reminding them of the study was sent during the beginning of the fourth week of the Fall 2018 semester with a deadline of Sunday to participate in the survey.

To increase data accuracy, the researcher used Qualtrics to store a unique course and instructor identifier to generate the recruitment URL. When the teacher distributed the URL to his or her students, the researcher was able to identify which section the student said they were enrolled in by the nature of clicking on the link. This proved invaluable because the researcher was able to verify student enrollment with the universities.

Institutional record data collection. The researcher only collected registrar data from those participants who consented to the study by taking the survey. The researcher contacted the registrar's office at the participating institutions at the end of the Fall 2018 semester following survey data collection by making two requests to each institution (see Appendix I). First, a spreadsheet with the student's name, student identification number provided, and signature authorizing FERPA data collection was sent with three missing data values: (1) Final grade in the online developmental mathematics course the student earned for the Fall 2018 semester. (2) Last date attended if the student withdrew or had an unofficial withdraw (as reported by the student's instructor). (3) A yes/no answer on if the student enrolled in a Mathematics course for the Spring 2019 semester? Second, a grade distribution by percent and/or letter grade for every developmental online course in the Fall 2018 semester – which was the same 49 courses identified at the beginning of the semester. Care was taken to make sure the registrar knew that those documents were FERPA compliant.

The grade of ‘C-’ or higher was determined to be the threshold for passing. Some institutions of higher education have differing levels of completion with some only accepting ‘C’ or better and others allowing ‘C-’. As well, some universities in the study did not provide ‘C-’ grades. The grade of ‘C-’ was earned by 2% of the population and sample. The researcher decided to include this group as passing. Small modifications to the results would happen if ‘C’ was alternatively chosen as the threshold grade.

The researcher took about three months to finalize the collection of the institutional record data due to unique rules and policies at each institution. Since the researcher was collecting FERPA protected data there were increased security measures and protections. Some institutions provided the data right away while other institutions required vice president, FERPA committee, or Institutional Research sign off before allowing the researcher to receive the requested data. Seven of the eight institutions ultimately provided the FERPA protected data. One institution stated institutional policy on the reason to not share the FERPA private data. In this particular case, the researcher emailed all the students from that university who had taken the survey and requested the answer to the 3 questions of final grade, date last attended, and if they were enrolled in a math class for the Spring 2019 semester. Fifteen of the 22 participants responded to the request for the institutional record data. The final usable data set included 330 participants.

Data Analysis

The researcher performed the analysis in two major steps. First, the researcher prepared raw data into factor values for each participant. Second, the researcher ran preliminary analyses by validating the survey instrument by conducting a 2-level confirmatory factor analysis (checking both clustered by universities and clustered by courses) based on the hypothetical instrument structure. Next, internal consistency for each of the subscale factors by finding the Cronbach alpahs. Preliminary analysis of descriptive tables, histograms, correlations, and intraclass correlations were also calculated. Lastly, using multilevel survival analysis and multilevel logistic regression the researcher answered each research question.

Data preparation. The researcher downloaded survey data collected from Qualtrics into Excel and created a unique identifier code for each student. The researcher then scored each of the three factors in the Community of Inquiry survey section (e.g., social presence, teaching presence and cognitive presence) by finding the means of the associated survey items in each category, as recommended by Arbaugh et al. (2008). If there were missing values, the researcher calculated the mean with the remaining items provided by the participant in pairwise deletion form. The researcher then classified each of the participants as perceiving a low, medium or high presence in their online course for each of the factors. The classification of low, medium, or high presence were identified by the tertile values. Tertile values were used to create three equal groups of data. Perception of high presence were data in the top third, low presence in the lower third and medium presence were data in the middle third. The researcher used this reclassified data when performing the Kaplan-Meier plots (Allison, 2010; Hosmer, Lemeshow, & May, 2011) and log-rank test during the survival analysis.

Using the MUSIC model user guide (Jones & Skaggs, 2016), the researcher scored each of the five motivation factors by calculating the mean of the items dealing with each category (e.g., eMpowerment, Usefulness, Success, Interest, and Caring). The researcher calculated any missing values with the pairwise deletion by taking the mean with the remaining items provided by the participant. Per the

Table 3.4

Overview of Research Questions, Data Sources, and Data Analysis Alignment

Research Question	Data Sources	Data Analysis
RQ 1: How does the online learning environment and student motivation predict student course persistence?	Qualtrics Surveys: (1) Community of Inquiry and (2) MUSIC model Registrar Course Completion Data (last date of academic activity for UW and withdrawal date)	Survival Analysis: Kaplan-Meier Plots, Log Rank Test, Cox Proportional Hazard Model
RQ 2: How does the online learning environment and student motivation predict student course completion?	Qualtrics Surveys: (1) Community of Inquiry and (2) MUSIC model Registrar Course Completion Data (Grade of C- or higher)	Multilevel Logistic Regression
RQ 3: How does the online learning environment and student motivation predict student mathematics retention?	Qualtrics Surveys: (1) Community of Inquiry and (2) MUSIC model Registrar Retention Data (enrolled in following semester)	Multilevel Logistic Regression

principles of the MUSIC model, it is meaningless to create one motivation value by adding all the values together. Prior research shows it is possible for students to be highly motivated and engaged when only one or two of the MUSIC model perceptions are high and others are low (Jones & Skaggs, 2016). The researcher then classified each of the participants as low, medium, or high motivation in each of the five categories using the tertile method described previously to create Kaplan-Meier plots (Allison, 2010; Hosmer et al., 2011) and log-rank tests for the survival analysis.

The researcher then conducted a factor analysis to verify the division of factors from both survey instruments using R (see Appendix J). Modifications and changes to the factors to improve alignment will be described in Chapter 4 as part of the data analysis. The reliability of each subscale was computed using R to find the Cronbach's Alpha score and ensuring that each factor had a value of .70 or higher.

The survey data preparation was developed before student course persistence and retention data were collected during the Fall 2018 semester. After the course persistence and retention data were collected, all values were combined to create one dataset. After institutional data were collected, the researcher connected the institutional registrar data to the survey data by matching student identification information and then stripped all identifying information from the dataset.

For the ease of survival analysis and logistic regression, failing students (receive a 'D' or 'F') and those who withdrew (either officially or unofficially) were grouped together. Analysis was performed in both R and SPSS to check accuracy of calculations. However, the researcher reported graphs and tables in this paper from R using R Studio to improve study replication.

Preliminary data analyses. The researcher performed a 2-level confirmatory factor analysis to check for validity and Cronbach alpha values for each factor to check for reliability. The analysis was clustered by school and then clustered by course to improve reporting accuracy (Pornprasertmanit, Lee, & Preacher, 2014). The researcher also analyzed descriptive statistic tables of the three learning environment and five student motivation factors to add understanding. Furthermore, histograms along with Skewness and Kurtosis for each of the eight factors were generated to understand the normal distribution for each of the factors. Correlation analysis between the factors was also performed to confirm theoretical relationship between learning environment and student motivational factors. Intraclass correlation analysis was also performed on the 2-level cluster of courses.

Data analyses. Table 3.4 provides an overview of the research questions, data sources, and data analyses.

Survival analysis. When measuring course persistence, the researcher analyzed the duration (i.e., time-to-event) to provide a deeper understanding of students' persistence. The statistical analysis strategy to measure an outcome with the duration to the outcome is survival analysis (Allison, 2010; Hosmer et al., 2011). Survival analysis is defined as a set of methods for analyzing data where the outcome variable is the time until the occurrence of an event of interest (Allison, 2010). This event can be death, occurrence of a disease, marriage, etc. (Hosmer et al., 2011). For this study, not successfully completing the course with a passing grade was the event measured. The multilevel survival analysis examined the time until that event took place.

For the survival analysis, a two-variable outcome is required. The first variable is a binary indicator (1 = dropout/failure; 0 = course success). In this study success is defined as a grade sufficient to move to the next mathematics course according to institutional standards. In survival analysis, this is referred to as lack of an event, or right-censoring (Allison, 2010). The second variable denotes the time-to-event or right-censoring (i.e., percentage of the semester duration). This is calculated as the course start date to date of withdrawal for those who officially withdraw, course start date to last date of academic activity for those who unofficially withdraw, and course start date to course end date for all other participants.

Analysis included Kaplan-Meier (KM) Plots, with associated log-rank tests, and Cox Proportional Hazard (PH) regression models (Allison, 2010). The researcher used the KM model for stratified factors of low/med/high of the different learning environment and motivation factors to isolate potential factors related to survival on course persistence. Variables exhibiting evidence of differential survival were incorporated together within the multivariate Cox PH regression models. One limitation to the Cox PH model is that variables do not change over time (Allison, 2010). Therefore, one assumption with this method was that the learning environment and motivation were constant throughout the remainder of the course. While some variability may exist, this limitation is acceptable in the analysis as the course design and online instruction are usually very consistent in the short duration of a semester.

Taking into consideration that students are part of cluster groups as courses, and within groups of universities that have differing enrollment procedures, it is difficult to conclude that the population is homogeneous. Heterogeneity can be explained by covariates or possibly through frailty models, which is a modification of the Cox PH model. Checks were made to determine the best optimal analysis of the data based upon the sample size and participating universities in the study.

To take multilevel (or mixed methods) into consideration, statistics were completed using R 3.6.1 (R Core Team, 2019) and packages of function coxph (with clustering) inside the package survival (Therneau, 2019a), and package coxme (Therneau, 2019b) with both the unique school and unique course inputted into the models. Methodology and approach were derived from the tutorial provided by Austin (2017). The full reproducible code is available in Appendix J. The importance of this analysis was to improve inference as a traditional regression model treats the units of analysis as independent observations (Rasbash, 2017). However, the analysis did not evaluate the frailty or analyze group comparison. The IRB approval and consent explicitly stated that comparison between schools and courses was not the object of this research study.

Multilevel logistic regression. To answer the questions of course completion and course retention, the researcher conducted analyses with multilevel logistic regression with the outcome variable being the binary term pass/no pass following the three-step pattern described by Sommet and Morselli (2013). The purpose of this added analysis of course completion to the similar measurement of course persistence was to compare the results from a purely nested, 3-level survival analysis (students within courses within universities) and a similar purely nested, 3-level logistic regression to improve interpretations of the data and results.

The researcher measured student mathematics retention with the outcome variable as two possible categorical outcomes for the Spring 2019 semester: (1 = successfully enrolled in a mathematics course; 0 = not enrolled in a mathematics course).

The researcher checked assumptions associated with the data to verify the multilevel logistic regression was a good fit model (Cohen, Cohen, West, & Aiken, 2003). First, the researcher verified that the dependent variable of retention was binary. Second, the researcher determined there should be little to no multicollinearity among the independent variables. After assumptions were met, the researcher analyzed the data using multiple logistic regression. Multiple logistic regression finds the equation that best predicts the value of Y based on the values of the X variables (Cohen et al., 2003). The researcher used R to purposefully select predictor variables of the learning environment and motivation factors to determine the dichotomous outcome variable of student completion or student retention. The researcher estimated the probability of the outcome variable by linking to the variables of the learning environment and motivation. The researcher reported the estimated coefficients, confidence intervals, and the goodness-of-fit from the model.

Because of the number of institutions (i.e., the eight university cluster groups) and number of courses (i.e., the 36 course cluster groups), the differences between the institutions made it difficult to assume homogeneous, or independent characteristics. One example is the differing enrollment procedures at each of the institutions of higher education. To take this into consideration, analyses were run in R and some analyses run in SPSS for verification purposes (only the R work is reported in Appendix J). The researcher used the three-step procedure to run multiple logistic modeling as explained by Sommet and Morselli (2013). The researcher verified the best model of the differing purely nested, 3-level logistic regression types to determine the best option for data analysis.

To take nesting into consideration with the eight clustered universities and 36 clustered courses, the multilevel logistic regression approach was used (Hox, Moerbeek, & Van de Schoot, 2017; Schwartz & Barrett, 2019). Statistics were done using R 3.6.1 (R Core Team, 2019), RStudio version 1.2.5033 and the lme4 1.1-21 (Bates, Mächler, B., & Walker, 2019) package. The full reproducible code is available in Appendix J. Similar Odds Ratios of fixed effects in the purely nested, 3-level logistic regression were generated and reported.

Ethical Considerations

The researcher stored a downloaded spreadsheet with the data inside a password protected Box account. All reported data, both oral and written, were recorded as aggregate data. The researcher gave privacy and protection information to the participants in the form of a consent letter before participants took the survey.

The researcher collected student consent to participate in the study in the Qualtrics survey they submitted. The researcher removed identifying data once the survey data had been connected with the course persistence and retention data.

An additional ethical consideration was the length of the survey instruments. Participants filled out a survey with 60 Likert-style questions which may have caused fatigue. This fatigue may have had a negative effect on the data and results. To help reduce potential stress, the researcher provided Qualtrics survey completion tracking, informed students how much time should be expected to take the survey, and provided incentives.

Limitations and Delimitations

Nonresponse Error

One of the data points collected in the study was the last date of attendance or academic activity, as determined by the Instructor, in each course if the grade of UW was awarded. These data were essential to perform the survival analysis and there was a possibility that instructors may have reported these dates differently. Because this date is consistent with national financial aid policies, the researcher reminded instructors to be as accurate as possible in reporting these dates and in accordance with their university policies regarding the UW grade.

Self-Reported Data Collection

When collecting the institutional data, one institution requested that the FERPA protected data be collected through student self-reporting. The researcher collected the students' final grades and if the student enrolled in the subsequent semester from 15 of the 330 students. There is a potential that this self-reported data were incorrectly reported to the researcher from the students. Considering there were no incentives or advantages provided to the 15 who reported the data, it is unlikely that many would have reported something differently. However, it is a limitation that should be disclosed.

Course Perception Data

Data in the study were collected from participants who were 18 years or older and enrolled in an online developmental mathematics courses at a university in Utah, which limited the diversity of the population demographics. Data were collected at the beginning of the third and fourth weeks of the semester after the students had some time to gain perceptions of the course. However, participants may not have had enough time to gain a complete picture of their online mathematics course. This time frame was necessary to collect data before students decided to stop persisting in the course or dropped out.

Retention Data

Retention was determined by those who enrolled in the next mathematics course (or repeated the same mathematics course). The researcher collected data in the next consecutive semester, which does not consider all types of student retention. Consequently, students who postponed their progression of mathematics courses to a later semester were treated the same as those who dropped out. A student who was taking a break from mathematics and may have enrolled in a future semester could not be accurately captured for this study.

Survey Instruments Chosen

The Community of Inquiry framework (Arbaugh et al., 2008) was used to measure the learning environment and the MUSIC model (Jones, 2009, 2018) to measure motivation. There are many other frameworks which have been used to measure aspects of the learning environment and motivation which were not selected for this study. Instead of measuring the actual features of the online learning environment, students answered survey questions with their perceptions of the online learning environment and motivation. The gap between student perceptions, teacher perceptions, and actual course features may have been greater than what the participants reported, but was beyond the scope of this study. However, this delimitation aligns with the theoretical framework of personality behavior to persist or drop a course. Mischel (2004) states that students use their cognitive processes to interpret the situation and then behave in accordance with that interpretation.

CHAPTER 4

RESULTS

The purpose of this study was to examine how student perceptions of the online learning environment and student motivation predicted course persistence, course completion, and mathematics retention in developmental mathematics courses. A quantitative, non-experimental, cross-sectional survey design was chosen to examine this relationship. This chapter outlines the results from the analyses including: (a) comparing pass rates from population to sample size, (b) preliminary data analysis results, and (c) findings from methods to answer each of the three research questions. For a comprehensive outline of all data analyses procedures, refer to Appendix J.

Pass Rates: Population vs Participants

To aid in understanding the validity of the data collected, the researcher collected the pass rates of the population (i.e., all identified online mathematics courses at public institutions of higher education in Utah) and compared it with the pass rates of the study participants (see Figure 4.1).

As Figure 4.1 shows, there was a higher percentage of participants in the study with A and B grades than the population overall. Additionally, there was a significantly lower percentage of participants in the study with F grades than the population overall distribution. This indicates a slight selection bias limitation in the study.

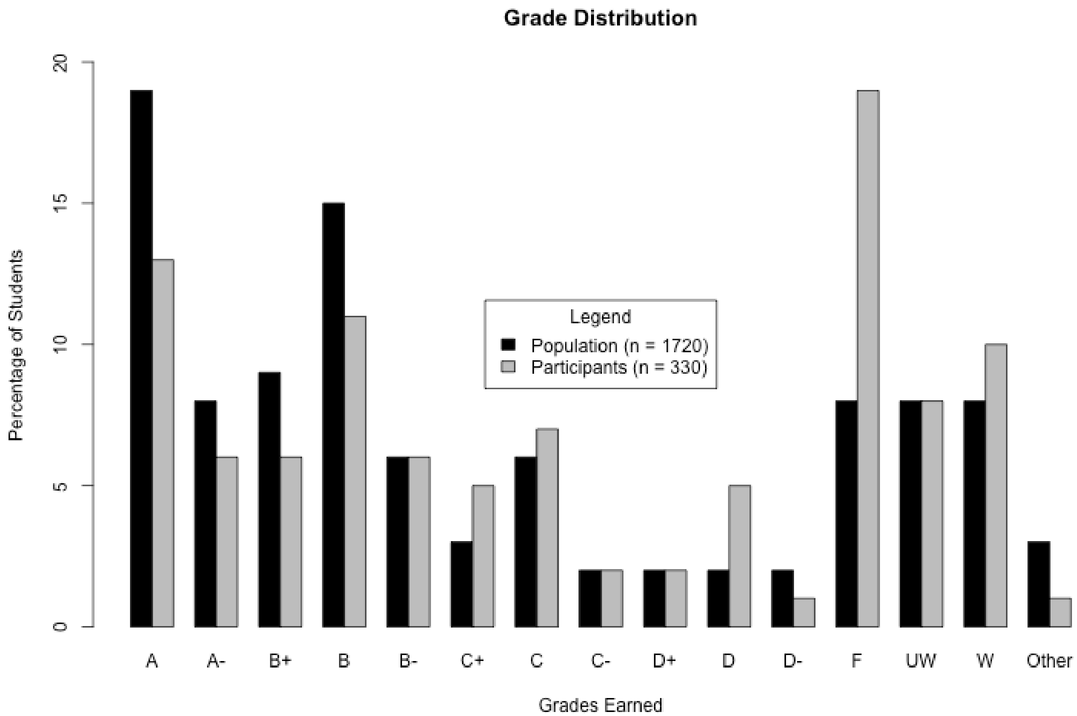

Figure 4.1. Pass Rates: Population vs Participants.

Preliminary Analysis of Factors

The researcher conducted a confirmatory factor analysis, descriptive statistics table for factors, histograms, a table of Skewness and Kurtosis, and correlations of the factors to better understand the results.

Factor Analysis

The researcher developed a 2-level confirmatory factor analysis analyzing the eight factor scores of the learning environment and motivation from the survey questions. To take nesting into consideration (students within courses within universities), the analysis was clustered using the unique school and course variables (Pornprasertmanit et al., 2014). The cfa( ) function inside the lavaan package in R allows for one clustering variable. Therefore, the researcher ran the

2-level confirmatory factor analysis by clustering with universities and then ran the analysis again by clustering into course groups. These analyses found the same results for both clustered types and while it was not The four highlighted indices in this study are the model chi-square, root mean square error of approximation (RMSEA), confirmatory factor index (CFI), and standardized root mean square (SRMR). The model chi-square had a value of $p < .001$. However, you want to see the *p*-value be greater than .05 for this to be a good fit. The RMSEA value should be less than .08 to indicate good fit and the analysis performed performed in Appendix J found the model to have a value of .079 which is borderline on being a good fit. The CFI should be greater than or equal to .90 and the model in this study was at .799 which did not make the cut-off. A SRMR good-fit should be less than .08 and this model had a value of .067 which did make the cut-off. Overall, of the 4 common factor indices chosen, 2 passed the test and 2 did not. The chi-square measurement is an absolute fit index and with the complexity of the model along with sample size this limits the ability to find an absolute goodness of fit model. The small discrepancies of the other three reported indices (two meeting the threshold and one not) is most likely due to the model complexity.

For an exploratory study of this nature, measuring eight different factors and 60 items, there are issues with good fit of the model due to model complexity. Using the data to find factors that have association to course persistence and retention and modifying the model to improve the fitness would result in more valid data in future studies.

The researcher calculated the Cronbach alpha for each factor to check for reliability. Cronbach alpha analysis is a single-level analysis, so nesting was not taken into consideration on this calculation. A value of .7 or higher is considered to be acceptable in social science research. Table 4.1 summarizes the results.

Table 4.1

Cronbach's Alpha for the Factors

Factor	Alpha
eMpowerment	.91
Usefulness	.91
Success	.91
Interest	.91
Care	.90
Teaching Presence	.94
Social Presence	.91
Cognitive Presence	.94

The calculated Cronbach alphas for the three learning environment factors and the five motivational factors were higher than 0.90, which indicated that there was internal consistency and reliability between the items used to measure the factors. However, high intercorrelations (i.e., Cronbach alpha values) might indicate that the items are "overly redundant and the construct measured too specific" (Briggs & Cheek, 1986, p. 114). Therefore, the concern for this study is that, with 60 measured items, there may have been redundant items in the instrument. This is particularly true with the learning environment factors of Teaching Presence (0.94) and Cognitive Presence (0.94).

Descriptive Statistics of Factors

The researcher created a descriptive statistics table for each of the three learning environment factors and five motivational factors (see Table 4.2) and grouped participants according to those who completed the course with a 'C-' grade or higher and those who did not. This table showed no significant groupings for the factor retention (see Table J.2). Appendix J contains histograms (see Figures J.1, J.2, J.3, J.4, J.5, J.6, J.7, J.8) as well as Skewness and Kurtosis (see Table J.3) along with interpretations. As these statistics are preliminary analyses for interpretation of the data, nesting was not taken into consideration.

Table 4.2

Descriptives of Measures by Course Completion

		Course Completion	
	Total n = 330	Completed n = 226	Did Not Complete n = 104
eMpowerment	4.935 (0.986)	4.975 (0.927)	4.849 (1.102)
Usefulness	4.621 (1.042)	4.705 (0.983)	4.437 (1.145)
Success	5.039 (0.909)	5.129 (0.817)	4.843 (1.060)
Interest	4.461 (1.011)	4.539 (0.962)	4.292 (1.096)
Care	5.338 (0.674)	5.350 (0.657)	5.311 (0.710)
Teaching Presence	4.951 (0.799)	4.945 (0.790)	4.964 (0.822)
Social Presence	4.223 (1.037)	4.162 (1.031)	4.356 (1.043)
Cognitive Presence	4.549 (0.902)	4.577 (0.851)	4.487 (1.006)

Note. Cell contains *M (SD)* for each category

The mean and standard deviation for each of the eight factors indicates which were the highest perceived factors in the online developmental mathematics courses (see Table J.1). Motivational factors of Success and Care had the highest mean values of student perceptions (5.039 and 5.338 respectively). The lowest mean scores of student perceptions were Interest and Social Presence (4.461 and

4.223 respectively). An analysis looking at the mean and standard deviations for each variable grouping those that completed and those who did not complete the class for each of the eight factors. Almost all factors showed that students who completed the course, on average, had a higher mean value of perception except for Teaching Presence and Social Presence. Teaching Presence was almost equal in mean values while Social Presence indicated the highest amount of difference with a mean of 4.162 for students who completed the course compared to 4.356 for those who did not complete.

Correlations of Factors

Table 4.3 shows the results from the correlation analysis. Cohen suggests that d = 0.2 be considered a 'small' effect size, d = 0.5 represents a 'moderate' effect size and 0.8 a 'strong' effect size. As indicated by the table, there is a moderate to moderately-strong effect size for each of the eight factors with each other. This result means that the online learning environment and student motivation factors have a moderate to moderately-strong relationship with each other, which confirms the theoretical relationship between the personal and environment factors in the Triadic Reciprocal Causation theoretical framework from this study (Bandura, 1986).

Table 4.3

Means, Standard Deviations, and Correlations with Confidence Intervals

Factor	*M*	*SD*	1	2	3	4	5	6	7
1. eMpowerment	4.94	0.99							
2. Usefulness	4.62	1.04	0.56**						
			[.48, .63]						
3. Success	5.04	0.91	0.70**	0.55**					
			[.64, .75]	[.47, .62]					
4. Interest	4.46	1.01	0.66**	0.70**	0.65**				
			[.59, .72]	[.64, .75]	[.58, .71]				
5. Care	5.34	0.67	0.54**	0.44**	0.57**	0.56**			
			[.46, .62]	[.35, .53]	[.49, .63]	[.49, .63]			
6. Teaching Presence	4.95	0.80	0.54**	0.49**	0.50**	0.61**	0.77**		
			[.45, .61]	[.41, .57]	[.41, .58]	[.53, .67]	[.73, .81]		
7. Social Presence	4.22	1.04	0.43**	0.48**	0.40**	0.52**	0.42**	0.56**	
			[.33, .51]	[.39, .56]	[.30, .48]	[.43, .59]	[.33, .51]	[.48, .63]	
8. Cognitive Presence	4.55	0.90	0.52**	0.71**	0.51**	0.69**	0.46**	0.63**	0.72**
			[.44, .59]	[.66, .76]	[.43, .59]	[.63, .74]	[.37, .54]	[.56, .69]	[.67, .77]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014).
$^{*}p<0.05$; $^{**}p<0.01$

Nesting and Intraclass Correlations

The sample of students in the study came from 36 different courses in eight different universities. A purely nested, 3-level model analyzing students within courses within universities was developed. Intraclass correlations (ICC) were calculated by analyzing the eight factors within course groups. Table 4.4 provides these results of the correlation among observations with the same course (Koo & Li, 2016). For each of the eight factors analyzed, the ICC (1) value, which is the percentage of variance due to the course, ranged between 3% - 14%. ICC (2) values which are less than .5 indicate poor reliability, between .5 and .75 are moderate, between .75 and .9 are good, and higher than .9 is excellent (Koo & Li, 2016) The reliability of course differences, or ICC (2), for three of the factors was moderate (Usefulness, Interest, and Teaching Presence), while all the other factors indicate a poor reliability of course differences. This finding indicates that while multilevel analyses will provide a little benefit over a single-level model with this particular study sample, it will not be a dramatic difference.

Table 4.4

Intraclass Correlations Between and Within Courses

	ICC(1)	ICC(2)	M	U	S	I	C	TP	SP	CP
eMpowerment (M)	.07	.40	1.00							
Usefulness (U)	.14	.60	.77(.51)	1.00						
Success (S)	.04	.26	.63(.72)	.55(.55)	1.00					
Interest (I)	.13	.58	.81(.63)	.79(.68)	.71(.64)	1.00				
Care (C)	.03	.23	.47(.56)	.31(.48)	.49(.57)	.47(.59)	1.00			
Teaching Presence (TP)	.10	.50	.68(.51)	.52(.49)	.57(.49)	.67(.59)	.85(.76)	1.00		
Social Presence (SP)	.03	.21	.63(.39)	.57(.47)	.48(.38)	.67(.49)	.48(.41)	.58(.56)	1.00	
Cognitive Presence (CP)	.08	.44	.81(.46)	.80(.70)	.61(.50)	.78(.67)	.46(.46)	.66(.62)	.82(.71)	1.00

Note. ICC(1) = Intraclass Correlation 1 (Percentage of variance due to course groups).
ICC(2) = Intraclass Correlation 2 (Reliability of course group differences).
In the correlation table the values are represented as: Correlation between groups(Correlation within groups).

Student Course Persistence Analysis

Research Question 1

The first research question focused on relationships between students' perceptions of the online learning environment and student motivation and their course persistence. To answer this question, the researcher performed a survival analysis by creating Kaplan-Meier plots and running a Multilevel Cox Regression.

Survival Analysis: Kaplan-Meier Plots. The researcher first generated a Kaplan-Meier Plot for each of the eight factors. Using R software, a Kaplan-Meier plot was developed to visualize the survival over a period of time. The timeline for this study was determined to be the Fall 2018 semester (116 days). The researcher created Kaplan-Meier plots for each of the eight factor variables by using the tertile variables which separated the factors into "High", "Medium", and "Low" perception groups. The results indicated that the two factors (i.e., Success and Social Presence) showed significant promise for the Multilevel Cox Regression (see Figures 4.2 and 4.3; all Kaplan-Meier plots are included in Appendix J).

In Kaplan-Meier plots, probability of surviving to any point is estimated from calculating the cumulative probability of surviving each of the preceding time intervals and represents only an estimate of survival for a hypothetical cohort - not the actual percentage of surviving. In Figure 4.2, the survival probability graphs for each of the three groups do not cross each other frequently. If that happened, that behavior would reduce the significance value that could be determined in a Multilevel Cox Regression. Kaplan-Meier plots are a categorization of the continuous factors, which does not require multi-level analysis as it is more informative of which variables to analyze further in the multilevel Cox Regression

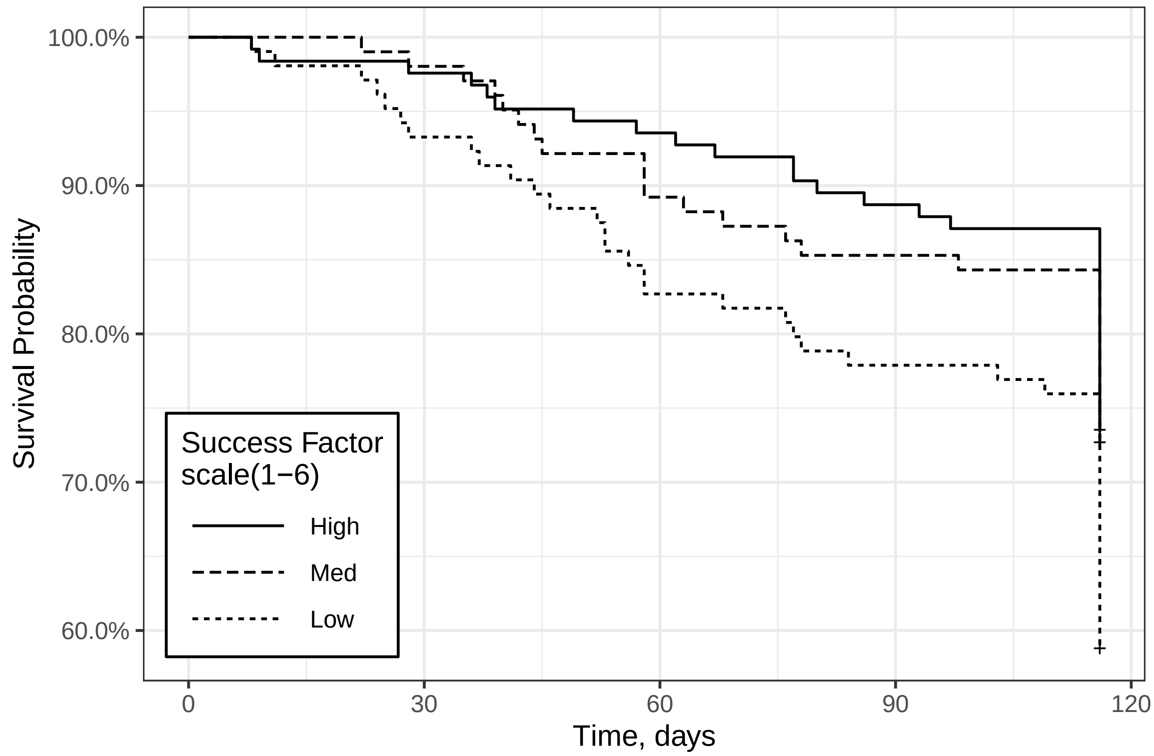

Figure 4.2. Kaplan-Meier plot of the Success factor of the MUSIC Model of Motivation measure model. Data divided by tertiles into High, Med, and Low groups.

analysis. As well, the drop off at the end of Figure 4.2 represents the students that received a D or F and therefore, did not meet the passing standard in the course.

The probability of survival for participants in the low Success perception group is generally lower than the medium perception group. Additionally, the medium Success perception group is generally lower than the high Success perception group as the semester continues. This finding indicates that participants who scored themselves higher on the Success factor were more likely to continue persisting in the course towards completion.

In Figure 4.3, the probability of survival rates for each of the three groups with differing perceptions of Social Presence follows a similar pattern to the Success factor. However, the low and high perception groups are switched. This finding

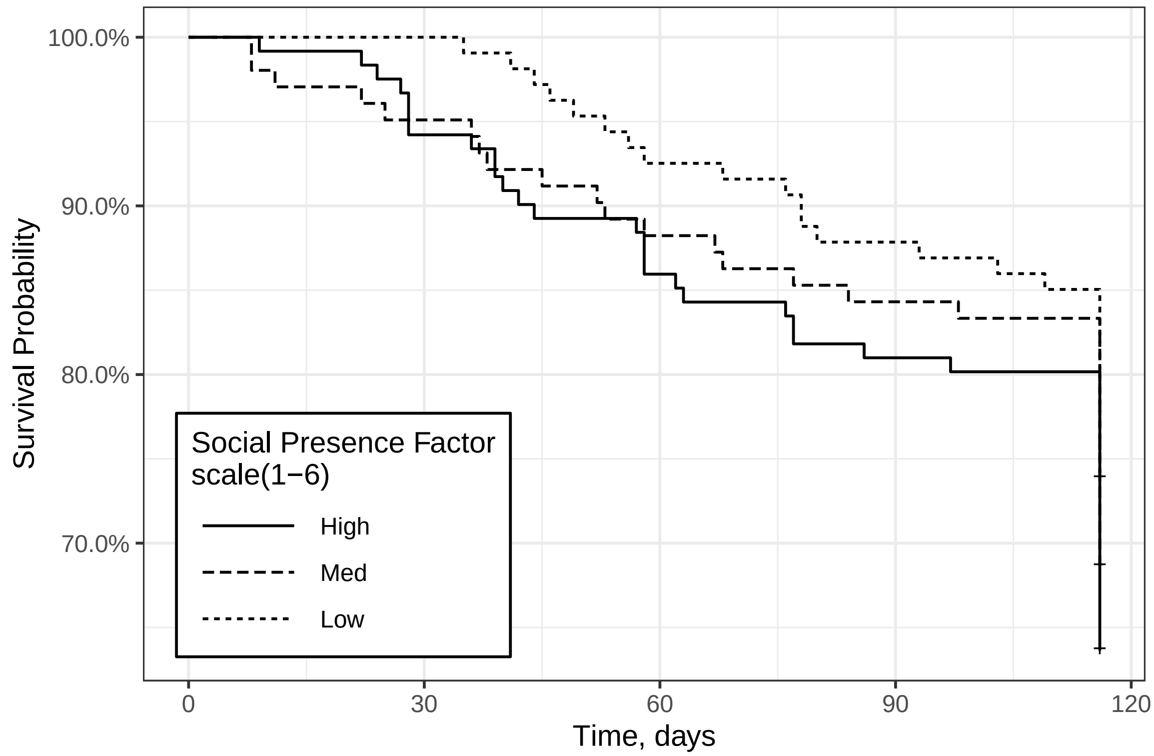

Figure 4.3. Kaplan-Meier plot of the Social Presence factor of the Community of Inquiry model. Data divided by tertiles into High, Med, and Low groups.

indicates that participants that perceive a higher Social Presence are more likely to dropout and not continue with their coursework.

Survival Analysis: Multilevel Cox Proportional Hazard Model. After analyzing the Kaplan-Meier plots, the researcher then generated purely nested, 3-level Cox Regression models for each of the eight variables (see Appendix J), and then started with the complete 8-factor model and used backward stepwise factor removal to get to the final 2-factor model with Success and Social Presence as the statistically significant factors (see Table 4.5 and Figure 4.4).

Multilevel Cox Regression is a good way to monitor course persistence for time-to-event or survival in a course. The backward stepwise factor removal process reduced the 8-factor model to a 2-factor model with the two factors of Success and Social Presence remaining. The likelihood test showed there was not a

Table 4.5

Multilevel Cox Proportional Hazard Regression Results for Course Persistence

	HR, Not Completing Course
Success	0.700 [0.565, 0.868]*
Social Presence	1.423 [1.143, 1.772]*
AIC	1141.005
BIC	1174.966
Log Likelihood	-557.660
Number not completed	104
N	330

Note. HR = hazard ratio, HR [95% CI], * 1 outside the confidence interval

significant difference between the 8-factor and 2-factor models. The researcher also checked the final model with the interaction between the two factors and found no significance and thus determined to not include the interaction in the final model for analysis.

Table 4.5 indicates a hazard ratio of 0.700 on the Success factor, which means that one point higher on student's perception of the Success factor corresponds to a 30% decrease in the log hazard rate. Likewise, a student's perception of the Social Presence factor scored one point higher corresponds to a 42% increase in the log hazard rate.

To visualize a representation of the Multilevel Cox Regression, three values are required to graph three lines for interpretation. The researcher chose quartile 1, the median (quartile 2), and quartile 3 to contextualize meaning in the visualization. Figure 4.4 is a virtual representation of this regression by showing how this relationship works with both variables. An increase of the hazard risk occurs as the students' perception of the Success factor decreases and the student's perception of the Social Presence factor increases.

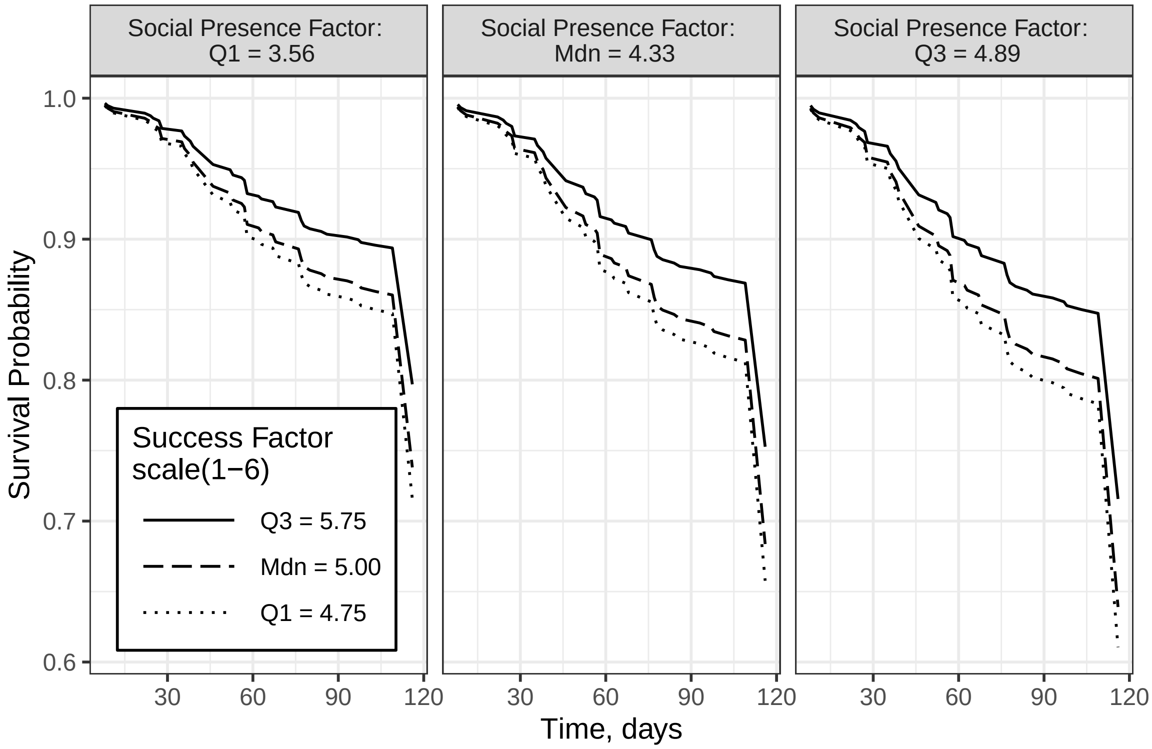

Figure 4.4. Survival analysis for course persistence in online developmental mathematics courses from final Multilevel Cox Proportional Regression analysis using coxph function in R package with clustering with unique schools. Lines divided with quartile breaks at first quartile, median, and third quartile for Success and Social Presence factors.

Student Course Completion Analysis

Research Question 2

The second research question focused on relationships between students' perceptions of the online learning environment and student motivation and these associations to their course completion. To answer this question, the researcher performed a multilevel logistic regression on student completion rates.

Multilevel logistic regression. The researcher measured the purely nested, 3-level logistic regression models for each of the eight independent factors to the dependent factor of student course completion. Then, the researcher started with the complete 8-factor multilevel logistic regression model and used the backward stepwise factor removal approach to arrive at the final 2-factor model. The interaction between the two variables were also checked, but did not show a significant effect on course completion. The final model results are displayed in Table 4.6. The full analysis is located in Appendix J.

Table 4.6

Multilevel Logistic Regression Results for Course Non-Completion

	OR, Not Completing Course
Reference: Success and Social Presence at grand means	0.396 [0.247, 0.632]*
Success	0.609 [0.447, 0.831]*
Social Presence	1.556 [1.165, 2.078]*
AIC	397.516
BIC	416.511
Log Likelihood	-193.758
N	330
Num. of Groups: Courses:Schools	36
Num. of Groups: Schools	8
Var: Courses:Schools (Intercept)	0.213
Var: Schools (Intercept)	0.158

Note. OR = odds ratio, OR [95% CI], * 1 outside the confidence interval

AIC = Akaike information criterion, BIC = Bayesian information criterion

These results indicate that a student with the grand means for both Success (5.039) and Social Presence (4.223) factors has a 40% chance of dropping out. Participants who perceive the Success factor one point higher correspond to a 39% reduction in the odds of dropping out. Participants who perceive the Social Presence factor one point higher correspond to a 56% increase in the odds of dropping out.

To visualize a representation of the multilevel logistic regression, three values are required to graph three lines for interpretation. The researcher chose quartile 1, the median (quartile 2), and quartile 3 to contextualize meaning in the visualization. Figure 4.5 demonstrates the visualization of this multilevel logistic regression.

Student Mathematics Retention Analysis

Research Question 3

The third research question examined the relationships among the students' perception of the online learning environment, student motivation, and course retention. The researcher measured the purely nested, 3-level logistic regression models for each of the eight independent factors (eMpowerment, Usefulness, Success, Interest, Care, Teaching Presence, Social Presence, Cognitive Presence) to the dependent factor of student retention in mathematics coursework. Similar to the analysis for research question 2, the researcher started with the complete 8-factor multilevel logistic regression model and used backward stepwise factor removal approach to arrive at the final 2-factor model. The analysis can be viewed in Appendix J.

Multilevel logistic regression. The researcher ran the model with taking school and course clusters into consideration in a purely nested, 3-level logistic

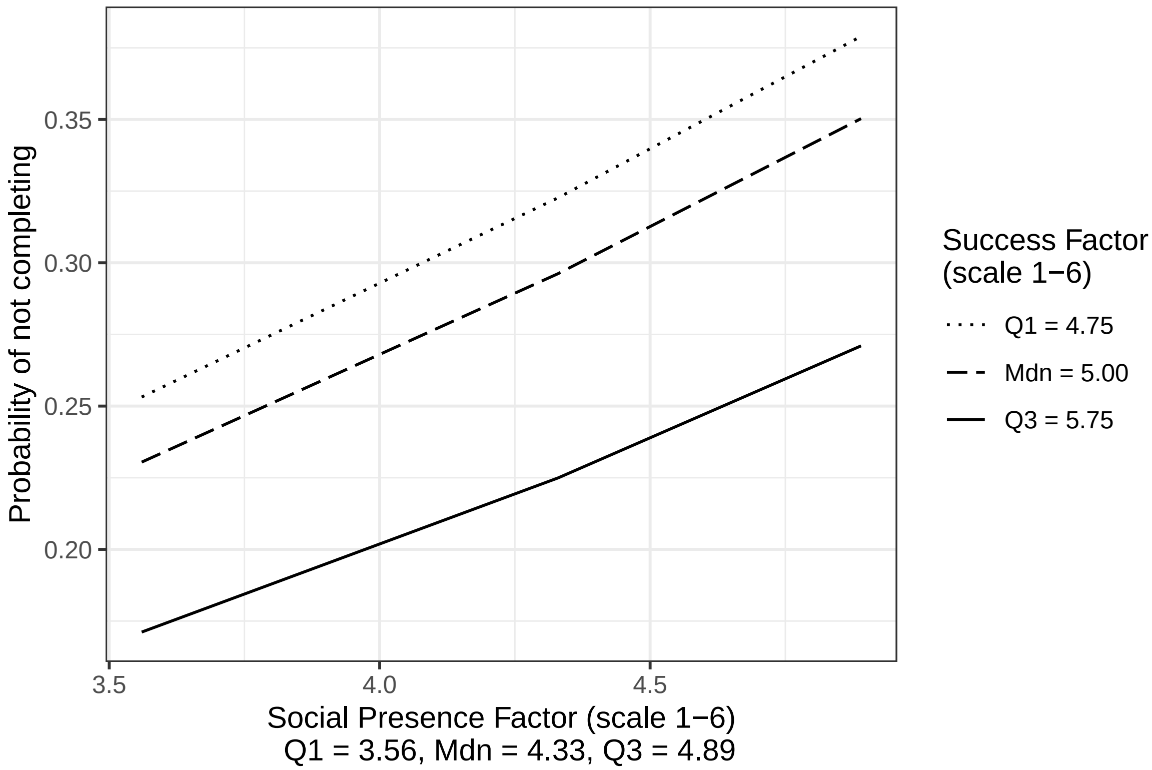

Figure 4.5. Odds probability of not completing online developmental mathematics course with multilevel logistic regression analysis. Lines divided with quartile breaks at first quartile, median, and third quartile for Success and Social Presence factors.

regression. Upon completion of the analysis of all models with different factors and factor removal, none of the models were a good fit or resulted in any significant predictable factors measured.

Summary

Findings from the study indicated the similarity between course persistence and course completion analysis. A 3-level Cox Regression and a 3-level logistic regression (students within courses within universities) similarly showed that students' perceptions of Success (motivation) and Social Presence (learning environment) factors played a role in student course persistence and completion.

The 3-level Cox Regression analysis indicated that students who scored one point higher on their perception of the Success factor corresponded to a 30% decrease in the log hazard rate. Additionally, students who scored one point higher in their perception of the Social Presence factor corresponded to a 42% increase in the log hazard rate. The multilevel logistic regression model found that a student with the grand means for both Success (5.039) and Social Presence (4.223) factors had a 40% chance of dropping out. Furthermore, students who scored one point higher on their perception of the Success factor corresponded to a 39% reduction in the odds of dropping out, while students who scored one point higher on their perception of the Social Presence factor corresponded to a 56% increase in the odds of dropping out. Finally, a 3-level logistic regression of the eight factors on student retention did not show any significant results.

CHAPTER 5

DISCUSSION

The purpose of this study was to examine how student perceptions of the online learning environment and student motivation predicted course persistence, course completion, and mathematics retention in developmental mathematics courses. Analyzing student perception data plays a role on their behavioral decision to add or drop the class. Analyzing students' perceptions of the online environment (Teaching Presence, Social Presence, and Cognitive Presence) and motivation (eMpowerment, Usefulness, Success, Interest, and Care) were identified for the purpose that an instructor or course designer could affect student course persistence and retention through understanding and modifications to online curriculum and instruction. Success and Social Presence were the two factors which showed significance and this chapter includes the interpretation and discussion of the results based on the three research questions. Implications for policy, practice, theory and research are discussed. In the final sections, the limitations of the study and possible future research stemming from this study are presented.

Learning Environment and Student Motivation

The preliminary analysis results showed moderate to moderately-strong effect sizes for each of the eight factors with each other. This finding confirms the theoretical framework of the relationship between self-perceived factors of the learning environment and the self-perceived factors of motivation in online developmental mathematics courses.

Each of the eight factors measured in the study (eMpowerment, Usefulness, Success, Interest, Care, Teaching Presences, Social Presence, and Cognitive Presence) had significant correlation to each of the other seven factors. This finding shows that there is a high likelihood that the online learning environment in developmental mathematics courses is correlated to student's motivation in the course. This finding indicates that the design of the online learning environment can potentially affect students' perceptions of the course in areas that can improve or diminish motivational factors.

This finding also increases the reliability of the instruments chosen for the study. The MUSIC® Model of Motivation (Jones, 2009) is a motivational and instructional model to help faculty in the design of their courses to increase student success by making them more motivated. The focus of the MUSIC model is on how the learning environment can improve motivation. The researcher chose the Community of Inquiry framework (Guilar & Loring, 2008) as the ideal online learning environment with a focus on student success. The fact that these two models are strongly correlated indicates that the scales used to determine the factors are closely aligned to similar outcomes.

This finding aligns with other research on curricular engagement with motivation (e.g., Kahu & Nelson, 2018; Schunk et al., 2008). As well, this finding supports the theoretical framework suggested by Bandura (1986) of the Triadic Reciprocal Causation model that personal factors and environmental factors are mutually interacting. There are more than 69 factors that researchers identified as contributing to online student dropout rates (Lee & Choi, 2011). Many of these factors are beyond the control of a faculty member and this research was focused on those factors which faculty and instructional designers could affect in curriculum and instruction that could predict course completion and retention.

There are concerns on the validity of the instruments as some of the goodness of fit analyses were met while others were not. For an exploratory nature of the study, with 60 items and eight factors from two different surveys, there was potential overlap on the questions. Further exploratory factor analysis research should be done on improving the survey instruments to increase the validity of these findings.

Student Course Persistence Analysis

The first research question focused on the association between the learning environment and motivation on course persistence.

Findings from the multilevel Cox Regression analysis in the study showed a one-point increase on the Success factor (scale of 1-6), corresponded to a 32% decrease in the likelihood of dropping out. Likewise, as students' score one-point higher on the Social Presence factor (scale 1-6), there was a 34% increase in the likelihood of dropping out (see Table 4.5).

These findings indicate that there is a positive correlation between the Success factor (Student Motivation) and student course persistence in online developmental mathematics. There also exists an inverse correlation between Social Presence factor (Learning Environment) and student course persistence in online developmental mathematics.

A study by Lewis et al. (2017) identified self-efficacy and sense of belonging as important factors to explain persistence intentions and actual persistence in Physical Sciences, Technology, Engineering, and Mathematics (pSTEM) coursework (more so for woman than men). Interactions with other students through social presence have been shown to improve sense of belonging in college courses (Delahunty et al., 2014). This would seem to confirm the findings from this study on the importance of Success and Social Presence to student persistence and completion. While other learning environment and motivational factors may prove valuable for overall enrichment and quality experience, the only predictors of course completion were Success and Social Presence.

Success Factor with Course Persistence

The Success factor in the MUSIC model determines the degree to which a student perceives that he or she can succeed in coursework. This is referred to as expectancy for success (Wigfield & Eccles, 2000) and builds off Self-Efficacy Theory (Bandura, 1977).

The Success factor was generated by having participants in the study rate responses on a Likert scale of 1-6 for the following statements:

1. I am confident that I can succeed in the coursework.
2. I feel that I can be successful in meeting the academic challenges in this course.
3. I am capable of getting a high grade in this course.
4. Throughout the course, I have felt that I could be successful on the coursework.

Higher scores on the Success factor scale indicate that students were more confident that they would succeed in the course and that their prior knowledge and personal skills would help them be successful in completing the course with a high grade.

This study showed a possible likelihood that students' who perceive their ability to succeed in an online developmental mathematics courses will persist to the end of the course. It is also important to note that students who have successfully completed courses in the past will potentially be more confident in their ability to do so in the future, which in turn increases their likelihood of persisting and completing their current and future courses.

Social Presence Factor with Course Persistence

The Social Presence factor in the Community of Inquiry framework determines the ability of participants to identify with the community (e.g., course of study), communicate purposefully in a trusting environment, and develop inter-personal relationships by way of projecting their individual personalities.

The Social Presence factor was generated by having participants in the study rate responses on a Likert scale of 1-6 for the following statements:

1. Getting to know other course participants gives me a sense of belonging in the course.
2. I can form distinct impressions of some course participants.
3. Online or web-based communication is an excellent medium for social interaction.
4. I feel comfortable conversing through the online medium.
5. I feel comfortable participating in the course discussions.
6. I feel comfortable interacting with other course participants.
7. I feel comfortable disagreeing with other course participants while still maintaining a sense of trust.
8. I feel that my point of view is acknowledged by other course participants.
9. Online discussions help me to develop a sense of collaboration.

Higher scores on the Social Presence factor scale show that students were more comfortable communicating and interacting with each other using the web-based tools to communicate. One of the downsides with the use of this particular survey instrument was that there were no ‘N/A’ options available to students on this survey. For example, some of the online developmental mathematics courses in this study did not have online discussions for students to interact with each other, therefore making an accurate representation of the social presence more challenging. It would be highly recommended that the survey instrument be modified to more accurately capture students perceptions of the social presence in their online developmental mathematics courses to make clearer interpretations.

This finding from this study was different than expected as the researcher hypothesized that those students who perceived higher amounts of social presence in the online learning environment would be more willing to persist through to the completion of the course.

The focus of the questions in the Social Presence factor determined the value students reported for social presence. Student collaboration in online courses can be done synchronously, asynchronously, or not at all. Faculty who responded to the researcher indicated they were teaching the online developmental mathematics courses in Fall 2018 semester, without requiring student-to-student interactions. Because of this finding, the researcher concluded that students did not persist in the course because of the lack of social presence opportunities provided in the course curriculum. A rival hypothesis could be that students who perceive more social presence in the online courses are more likely to drop-out. The first hypothesis would suggest interventions of adding more social interaction into coursework, while the rival hypothesis would suggest convincing students to construct more independence and rely less on other students for their learning.

The literature seems to side with the first hypothesis that students who feel isolated, or a lack of social presence, are more likely to not complete their course (e.g., Carr, 2014; Garrison et al., 2010; Oseguera & Rhee, 2009).

Students who have a higher perception of social presence in online developmental mathematics courses were more likely to not complete the course. The researcher believes that this finding is related to the design and implementation of the online developmental mathematics courses in this study, where social interactions with other students were not required. Some instructors explicitly told students they should form study groups, but other instructors took no intentional actions to encourage or support student interaction. None of the courses had designed and required group activities to encourage social interaction in online developmental mathematics courses. Understanding the complete level of social interaction students have with each other and how that relates to their willingness to persist in the course should be researched further and more complete.

The questions in the survey measured students' perception of the Social Presence factor and those who feel they can function better in that environment. To reach a stronger interpretation of the effect social presence has on student completion rates, the survey instrument should be modified and adapted to focus on measuring the social presence opportunities provided in the current online developmental mathematics course (rather than measuring general perceptions of social presence). Included in this should be the option for students to indicate they didn't perceive any social presence (including not applicable, N/A, options in the data collection).

Analysis of Course Persistence versus Course Completion

The second research question was developed to analyze the differences and similarities between course persistence (as measured with survival analysis in the first research question) and course completion (as measured with logistic regression in the second research question).

To demonstrate course completion, the researcher performed a multiple logistic regression analysis. The result of this analysis showed Success and Social Presence factors predicted 44% of the student drop out. Students who scored one point higher in the factor, Success, corresponded to a 41% reduction in the odds of dropping out. Students who scored one point higher in the factor, Social Presence, corresponded to a 48% increase in the odds of dropping out (see Table 4.6). These results indicate that students who perceive they will be successful in the class are more likely to complete the course successfully. However, students who perceive higher social presence in online developmental mathematics courses are more likely to not complete the course successfully.

These findings were similar when looking at Course Persistence (Survival Analysis and Multilevel Cox Regression) and Course Completion (Multilevel Logistic Regression). This finding indicates that both methodologies are similar for this study. The researcher concluded that, in this particular case, the multilevel multiple logistic regression and the multilevel Cox regression helped identify similar factors and variables through analysis and either method could be used interchangeably to answer similar research questions on course persistence versus course completion.

Student Mathematics Retention Analysis

The third research question focused on the predicting mathematical retention from the learning environment and motivation factors.

The results of the multiple logistic regression for this question indicated that none of the eight factors of the learning environment and motivation had a significant effect on student retention for the subsequent semester. The three learning environment factors (Community of Inquiry) and five motivational factors (MUSIC model) were factors that an instructor or course designer could affect through curriculum and instruction in online developmental mathematics. These findings show that students' perceptions of the online learning environment and curricular motivational factors were not associated with students' decisions to continue to study in future mathematics courses. While research shows that curricular engagement is recognized as crucial for learning and retention (Trowler & Trowler, 2010), the decision to enroll in a mathematics course in a future semester is likely influenced by other identified factors of retention (e.g., Berge & Huang, 2004; Lee & Choi, 2011). While ultimately the environment and motivational experiences a student has in their online developmental mathematics course will play a role in the holistic decision to continue taking mathematics courses, the Circumstantial, Personal, and Institutional Variables (outside of their previous coursework) (Berge & Huang, 2004) may have a more significant influence on a students' behavioral decisions.

One important note is that this study defined course persistence, course completion and mathematics retention as distinct definitions while sometimes in research these terms are used interchangeably. The methods of survival analysis for course persistence and multiple logistic regression for course completion resulted in similar results with a couple of significant factors. However, by using multiple logistic regression to measure those who enrolled in a mathematics course the subsequent semester resulted in no significant outcomes. This verified the concerns brought up by other researchers on the importance of clear definitions and reporting of attrition/dropout rates to measure interventions on course persistence and retention (e.g., Coleman et al., 2017; Lee & Choi, 2011; Pigliapoco & Bogliolo, 2008).

Implications for Course Persistence and Completion

The first two questions in the study looked at the predictability of the online learning environment and student motivation on course persistence and completion. Implications of these findings are discussed on policies/practice and theory/research.

Policies and Practice

The behavioral decision students make to persist to course completion or dropout from a course is determined by a variety of factors. Some of these factors are personal or circumstantial (such as personal finances, family concerns, etc.). Many of those factors are beyond the control of an institution of higher education or the faculty teaching a course. The curriculum and instruction factors of the learning environment and motivation derived from course design are things an instructor can control. As well, students' ability to overcome challenges and adversity from outside factors have the potential to be affected when there is higher self-efficacy and a sense of belonging through student interactions.

Institutions and faculty who wish to improve course persistence and student completion rates can focus on the development of initiatives that identify and build students' self-efficacy and confidence (characteristics of the Success factor). One example of efforts to improve student confidence is helping online developmental mathematics instructors apply aspects of Validation Theory. The research found that there were major differences between how low-income and traditional students experienced the transition into college. At some point, low-income students suddenly come to believe in themselves as capable college learners, not because of their college involvement, but because some person(s), inside or outside of college, took the initiative to reach out to them to help them believe in themselves and their innate capacity to learn. (Rendón, 1994; Rendón & Muñoz, 2011). The researcher's findings and results from this current study confirm the literature that the more students believe they are capable of succeeding in college coursework, the liklihood of them completing the course is also increased.

Furthermore, faculty and instructional designers can build and facilitate learning activities where students are required to interact and collaborate with their peers. The nature of teaching a face-to-face course often includes built-in opportunities for social interaction between students which has the potential to increase social presence perceptions from students. In an attempt to provide flexibility to students by allowing learning to be conducted at any time and any location, social interaction has been reduced in the curriculum design of the online environment. Implications of this instructional design could potentially decrease completion rates. Efforts to increase student interaction and social presence perceptions could support students in persisting and completing online developmental mathematics courses.

When designing and implementing social interactions with students in the online environment, caution for negative student interactions is also highly recommended. Research conducted by Gibson (2019) found that, while online student-to-student interactions (such as group work) can lead to successful outcomes, a majority of students complained about working with other peers in the online environment. For this reason, actions taken by faculty to build a sense of community with students in online developmental mathematics courses should work to reduce the negative effects of student interactions and efforts to build a sense of community and belonging. Building social presence does not necessarily mean course group work.

The sense of belonging students feel in an online learning environment has a role on course completion (Delahunty et al., 2014). While building a community in the learning environment is not a priority for all students, it does associate with course persistence and completion for the students that value the student-to-student interaction.

Theory and Research

The findings and results from this study indicate that there are connections between online course learning environment factors, student motivational factors, and students' behavioral decisions to persist and complete an online developmental mathematics course. Much research has been performed with self-efficacy and social presence. Further exploration is recommended on the identification of the students' perception of the success factor and social presence factor. As well, interventions that would have a changing effect on student perceptions through pre- and post-measures would provide valuable information. Furthermore, research on changes in course design to improve learning environment and student motivations from course design perceptions would have an effect on students' course persistence and completion. Evaluating course design projects and methods to discover what aspects of social presence work organically in online developmental mathematics courses without forcing assignments could increase social presence and support students who value that interaction. However, further research into online interactions are needed to improve best practices in an environment that demands flexibility.

Implications for Mathematics Retention

The third question in the study looked at the predictability of the online learning environment and student motivation on mathematics retention. Implications of these findings are discussed on policies/practice and theory/research.

Policies and Practice

This study showed that there was no link between students' perceptions of their course learning environment and the motivation they perceived with the ultimate decision to continue taking required mathematics courses leading towards graduation. The study did not find any statistical connection of the online learning environment to retention. Although there were no statistical relationships or prediction between the current online learning environment and motivation to registering for a mathematics course in the next semester, it would be impossible to do so without first successfully persisting and completing the current mathematics course.

Theory and Research

The findings also suggest that while there are factors and reasons a student does not continue the following semester with mathematics coursework, it is usually for reasons outside of the learning environment and personal motivational factors in the current coursework. Lee and Choi (2011) found a large range of factors (around 69) that play a role in student retention and the findings suggest that these factors have a stronger association than the learning environment and motivation from the current mathematics course.

Limitations

Generalizability of the Study

The study was limited to students in online developmental mathematics courses in eight public institutions of higher education under the Utah System of Higher Education (USHE). Because of the specificity of the population, it would be impossible to make generalizable interpretations beyond online developmental mathematics students in the Rocky Mountain region.

Nonresponse Error

One limitation of this study was the nonresponse error. The more likely a student was to drop out of an online developmental mathematics course, the more likely they were not to participate in the study. To reduce this concern, introductory letters building anticipation for the survey with an opt-in option were sent to all participants in the online courses (see Appendices B and C). Incentives were provided in the way of Amazon gift cards or credit depending on the preference of the instructor. Incentives were provided within 48 hours after participants completed the survey.

As shown in Figure 4.1, there was a higher percentage of A/B students who participated in the study than in the general population. Additionally, there were less F/UW/W students who participated in the study. Even with incentives offered, the study sample was not a direct match to the general population. However, the grade distribution plot of participants aligned similarly to the overall population of online developmental mathematics students.

Potential Instructor Reporting Errors

Course persistence was measured over time (116 days of the semester). Time-to-event, or survival, is limited on correct reporting of the drop date. The researcher reminded instructors to be as accurate as possible in reporting these dates and in accordance with their university policies regarding the withdrawal or unofficial withdrawal reported dates.

Recommendations for Future Research

Finding ways to build student-to-student interactions in online environments can be challenging. Lovell and Elakovich (2016) found that building face-to-face interactions with students while taking a Massively Open Online Course (MOOC) encouraged completion, even though MOOCs are associated with high dropout rates. However, many students take online courses for the time and location flexibility offered and would not have the ability to attend face-to-face coursework activities that a blended modality would offer. Future research should look into how to effectively implement social interactions in the online environment and if those interactions have a positive effect on student course completion rates.

Furthermore, studies are needed on which type of online course activities and interventions would support online students who have a higher value perception of social presence. While the literature showed positive effects of social presence in online coursework in general, there was a lack of research in online developmental mathematics courses. This study showed the importance of continuing research on best practices and Scholarship of Teaching and Learning in student-to-student interactions in online developmental mathematics to support students who have higher perceptions of social presence in the online learning environment.

Because of the student demand for online learning, it is important that comparative studies, between online courses with activities designed with attributes of social presence, be compared to other traditional independent online courses. A face-to-face course would have social presence automatically built in by the nature of meeting at the same time and location. It is important to study how to design online developmental mathematics courses that provide support, encouragement, and interactions that students perceive will add to an enhanced learning experience and potentially higher course completions.

In addition, future studies could include gathering instructor reported information on course design elements and activities. The purpose would be to compare the intended and enacted curriculum strategies in the online developmental mathematics environment with students perceptions of the learning environment. This research would aid practitioners on knowing if the intended and enacted curriculum is having desired perception on students learning experience.

Conclusion

This study showed a connection between the online learning environment and student motivation in online developmental mathematics courses. This correlation and connection showed the value for faculty to continue to develop best practices and to support students' in online learning. Of the three different learning environment factors and five motivational factors, the Success motivational factor (or self-efficacy) and Social Presence learning environment factor had the most significant effect on student persistence and completion in the online developmental mathematics courses in this study. There were no effects found for any of the eight variables on student retention in taking mathematics classes during the following semester. Efforts and interventions geared towards building student self-efficacy and designing more student-to-student interactions have the potential to increase course completion rates in online developmental mathematics courses.

Students' behavioral decisions to dropout of a course are tied to many factors, which may be outside of the control of the university and faculty (e.g., financial, health, family, etc). Building self-efficacy in one's confidence to complete an online developmental mathematics course, and a positive support group of fellow classmates, has the potential to give students the tools necessary to successfully navigate the unforeseen challenges they may encounter during their university experience.

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APPENDICES

Appendix A

Institutional Review Board (IRB) Letter of Approval

Appendix A: Institutional Review Board (IRB) Letter of Approval

UtahState University
OFFICE OF RESEARCH AND GRADUATE STUDIES

Institutional Review Board

USU Assurance: FWA#00003308

Expedite #7

Letter of Approval

FROM:

Melanie Domenech Rodriguez, IRB Chair

Nicole Vouvalis, IRB Administrator

To:	Patricia Moyer-Packenham, Samuel Gedeborg
Date:	August 23, 2018
Protocol #:	9510
Title:	Relationships Between The Learning Environment, Student Motivation, And Course Persistence And Retention: Students' Perceptions Of Online Developmental Mathematics Coursework
Risk:	Minimal risk

Your proposal has been reviewed by the Institutional Review Board and is approved under expedite procedure #7 (based on the Department of Health and Human Services (DHHS) regulations for the protection of human research subjects, 45 CFR Part 46, as amended to include provisions of the Federal Policy for the Protection of Human Subjects, November 9, 1998):

> Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies. This approval applies only to the proposal currently on file for the period of one year. If your study extends beyond this approval period, you must contact this office to request an annual review of this research. Any change affecting human subjects must be approved by the Board prior to implementation. Injuries or any unanticipated problems involving risk to subjects or to others must be reported immediately to the Chair of the Institutional Review Board.

This approval applies only to the proposal currently on file for the period of one year. If your study extends beyond this approval period, you must contact this office to request an annual review of this research. Any change affecting human subjects must be approved by the Board prior to implementation. Injuries or any unanticipated problems involving risk to subjects or to others must be reported immediately to the Chair of the Institutional Review Board.

Prior to involving human subjects, properly executed informed consent must be obtained from each subject or from an authorized representative, and documentation of informed consent must be kept on file for at least three years after the project ends. Each subject must be furnished with a copy of the informed consent document for their personal records.

4460 Old Main Hill | Logan, UT 84322-4460 | PH: (435) 797-1821 | Fax: (435) 797-3769 | WEB: irb.usu.edu | EMAIL: irb@usu.edu

Appendix B

Survey Instrument

Appendix B: Survey Instrument

Digital copy of survey can be previewed at: `https://usu.co1.qualtrics.com/jfe/preview/SV_ahjIxfbNX6RISGh?Q_CHL=preview`

Purpose of the Study:

You are invited to participate in a research study conducted by Patricia Moyer-Packenham, a Professor in the School of Teacher Education and Leadership at Utah State University. The purpose of this research is to understand students' perceptions of their online mathematics course and relationships to course persistence and retention.

This form includes detailed information on the research to help you decide whether to participate in this study. Please read it carefully and ask any questions you have before you agree to participate.

Procedures:

Your participation will involve the completion of a survey (6 groups of 10 questions) and some demographic questions. Completion of the survey will take approximately 10 - 15 minutes. If you agree to participate, the researchers will also collect information about your completed online mathematics course and future enrollment in a mathematics course during the subsequent semester from the Registrar's Office at your institution.

We anticipate that XXX people will participate in this research study at this site, and that a total of 400 people will participate among all 8 sites.

Risks:

This is a minimal risk research study. That means that the risks of participating are no more likely or serious than those you encounter in everyday activities. The foreseeable risks or discomforts include fatigue from filling out a survey, loss of confidentiality, and loss of privacy. In order to minimize those risks and discomforts, the researchers will keep the survey length to 10 – 15 minutes and break it up into 7 parts. The researchers will also make sure to securely store as outlined in the Confidentiality area below. If you have a bad research-related experience, please contact the principal investigator of this study right away at (435)797-2597 or `patricia.moyer-packenham@usu.edu`.

Benefits:

Participation in this study may directly benefit you by making you aware of your perceptions of online mathematics course and your engagement with the online course may increase. More broadly, this study will help the researchers learn more about how students perceive the online coursework and may help future educators and students improve the quality of online mathematics courses.

Confidentiality:

The researchers will make every effort to ensure that the information you provide as part of this study remains confidential. Your identity will not be revealed in any publications, presentations, or reports resulting from this research study. We will collect your information through Qualtrics, and through your Registrar's Office. This information will be securely stored in Qualtrics, a restricted-access folder on Box.com, an encrypted, cloud-based storage system, or in a locked drawer in a restricted-access office. Once your survey data are connected with your academic records data (which will be collected in the subsequent semester), all identifiers will be separated out and destroyed. Records of your agreement to participate in this study will be kept for three years after the study is complete, and then will be destroyed.

It is unlikely, but possible, that others (Utah State University, or state or federal officials) may require us to share the information you give us from the study to ensure that the research was conducted safely and appropriately. We will only share your information if law or policy requires us to do so.

Voluntary Participation & Withdrawal:

Your participation in this research is completely voluntary. If you agree to participate now and change your mind later, you may withdraw at any time by contacting the researchers and requesting to be removed from the study. If you choose to withdraw after we have already collected information about you, we will remove your data as long as the request has been made before we remove identifying information (which will be completed in the subsequent semester). If you decide not to participate, the services you receive from your online mathematics course will not be affected in any way.

Compensation:

Agreement for Collecting Registrar Office Data:

Upon signing this consent form you are agreeing that the researchers may reach out to the Registrar's Office to gather data on you for the following items:

(1) The grade you received in the online mathematics course -or- your withdrawal date -or- your unofficial withdrawal date.

(2) Your enrollment status in a mathematics course for the subsequent semester.

IRB Review:

The Institutional Review Board (IRB) for the protection of human research participants at Utah State University has reviewed and approved this study. If you have questions about the research study itself, please contact the Principal Investigator at (435) 797-2597 or `patricia.moyer-packenham@usu.edu`. If you have questions about your rights or would simply like to speak with someone other than the research team about questions or concerns, please contact the IRB Director at (435) 797-0567 or `irb@usu.edu`.

Patricia S. Moyer-Packenham, PhD

Principal Investigator

(435) 797-2597; `patricia.moyer-packenham@usu.edu`

Samuel K. Gedeborg

Student Investigator

(801) 210-0162; `sgedeborg@aggiemail.usu.edu`

Participant Consent:

[___] Yes, I have read the material and agree to participate

[___] No, I do not agree to participate

Required Information: If you agree to participate, please provide the following information to begin the 10-15 minute survey:

First Name: [______________________________]

Last Name: [______________________________]

Your Student ID Number

(to request grade/enrollment status from registrar office):

[______________________________]

Which email address can we send your $5 Amazon Gift Card to?

(Enter `none@email.com` if you wish to participate in the study, but not receive the gift card).

[______________________________]

Please sign below showing that you agree to have the researchers contact the Registrar's Office to release (1) the grade/outcome you received in the online mathematics course and (2) your enrollment in a mathematics course for the subsequent semester. These data will be used to measure course persistence and retention and will be highly protected as outlined in the consent form.

[______________________________] (Signature Box)

PART 1 of 7

Please rate the items in this section using the given scale.

(1=Strongly disagree, 2=Disagree, 3=Somewhat disagree, 4=Somewhat agree,

5=Agree, 6=Strongly agree).

Note that the word "coursework" refers to anything that you do in the online mathematics course, including assignments, activities, readings, etc.

<*There is code after each statement to indicate which factor it belongs to.* **(M)** *for eMpowerment,* **(U)** *for Usefulness,* **(S)** *for Success,* **(I)** *for Interest, and* **(C)** *for Care. Participants did not see these comments and it is provided here to help the reader of Appendix B gain further understanding of the factors.*>

1. [___] The coursework holds my attention. **(I)**
2. [___] I have the opportunity to decide for myself how to meet the course goals. **(M)**
3. [___] In general, the coursework is useful to me. **(U)**
4. [___] The instructor is available to answer my questions about the coursework. **(C)**
5. [___] The coursework is beneficial to me. **(U)**
6. [___] The instructional methods used in this course hold my attention. **(I)**
7. [___] I am confident that I can succeed in the coursework. **(S)**
8. [___] I have the freedom to complete the coursework my own way. **(M)**
9. [___] I enjoy the instructional methods used in this course. **(I)**
10. [___] I feel that I can be successful in meeting the academic challenges in this course. **(S)**

PART 2 of 7

Please rate the items in this section using the given scale.

(1=Strongly disagree, 2=Disagree, 3=Somewhat disagree, 4=Somewhat agree,

5=Agree, 6=Strongly agree).

Note that the word "coursework" refers to anything that you do in the online mathematics course, including assignments, activities, readings, etc.

11. [___] The instructional methods engage me in the course. **(I)**
12. [___] I have options in how to achieve the goals of the course. **(M)**
13. [___] I enjoy completing the coursework. **(I)**
14. [___] I am capable of getting a high grade in this course. **(S)**
15. [___] The coursework is interesting to me. **(I)**
16. [___] The instructor is willing to assist me if I need help in the course. **(C)**
17. [___] I have control over how I learn the course content. **(M)**
18. [___] Throughout the course, I have felt that I could be successful on the coursework. **(S)**
19. [___] I find the coursework to be relevant to my future. **(U)**
20. [___] The instructor cares about how well I do in this course. **(C)**

PART 3 of 7

Please rate the items in this section using the given scale.

(1=Strongly disagree, 2=Disagree, 3=Somewhat disagree, 4=Somewhat agree,

5=Agree, 6=Strongly agree).

Note that the word "coursework" refers to anything that you do in the online mathematics course, including assignments, activities, readings, etc.

21. [___] I will be able to use the knowledge I gain in this course. **(U)**
22. [___] The instructor is respectful of me. **(C)**
23. [___] The knowledge I gain in this course is important for my future. **(U)**
24. [___] The instructor is friendly. **(C)**
25. [___] I believe that the instructor cares about my feelings. **(C)**
26. [___] I have flexibility in what I am allowed to do in this course. **(M)**

<*Start of* **Teaching Presence (TP)** *statements - participants did not see this comment and it is provided here to help the reader of Appendix B gain further understanding of the factors.*>

27. [___] The instructor clearly communicates important course topics. **(TP)**
28. [___] The instructor clearly communicates important course goals. **(TP)**
29. [___] The instructor provides clear instructions on how to participate in course learning activities. **(TP)**
30. [___] The instructor clearly communicates important due dates/time frames for learning activities. **(TP)**

PART 4 of 7

Please rate the items in this section using the given scale.

(1=Strongly disagree, 2=Disagree, 3=Somewhat disagree, 4=Somewhat agree,

5=Agree, 6=Strongly agree).

Note that the word "coursework" refers to anything that you do in the online mathematics course, including assignments, activities, readings, etc.

31. [___] The instructor is helpful in identifying areas of agreement and disagreement on course topics that helps me to learn. **(TP)**
32. [___] The instructor is helpful in guiding the class towards understanding course topics in a way that helps me clarify my thinking. **(TP)**
33. [___] The instructor helps to keep course participants engaged and participating in productive dialogue. **(TP)**
34. [___] The instructor helps keep the course participants on task in a way that helps me to learn. **(TP)**
35. [___] The instructor encourages course participants to explore new concepts in this course. **(TP)**
36. [___] Instructor actions reinforce the development of a sense of community among course participants. **(TP)**
37. [___] The instructor helps to focus discussion on relevant issues in a way that helps me to learn. **(TP)**
38. [___] The instructor provides feedback that helps me understand my strengths and weaknesses. **(TP)**
39. [___] The instructor provides feedback in a timely fashion. **(TP)**

<*Start of* **Social Presence (SP)** *statements - participants did not see this comment and it is provided here to help the reader of Appendix B gain further understanding of the factors.*>

40. [___] Getting to know other course participants gives me a sense of belonging in the course. **(SP)**

PART 5 of 7

Please rate the items in this section using the given scale.

(1=Strongly disagree, 2=Disagree, 3=Somewhat disagree, 4=Somewhat agree,

5=Agree, 6=Strongly agree).

Note that the word “coursework” refers to anything that you do in the online mathematics course, including assignments, activities, readings, etc.

41. [___] I can form distinct impressions of some course participants. **(SP)**
42. [___] Online or web-based communication is an excellent medium for social interaction. **(SP)**
43. [___] I feel comfortable conversing through the online medium. **(SP)**
44. [___] I feel comfortable participating in the course discussions. **(SP)**
45. [___] I feel comfortable interacting with other course participants. **(SP)**
46. [___] I feel comfortable disagreeing with other course participants while still maintaining a sense of trust. **(SP)**
47. [___] I feel that my point of view is acknowledged by other course participants. **(SP)**
48. [___] Online discussions help me to develop a sense of collaboration. **(SP)**

<*Start of* **Cognitive Presence (CP)** *statements - participants did not see this comment and it is provided here to help the reader of Appendix B gain further understanding of the factors.*>

49. [___] Problems posed increase my interest in course issues. **(CP)**
50. [___] Course activities pique my curiosity. **(CP)**

PART 6 of 7

Please rate the items in this section using the given scale.

(1=Strongly disagree, 2=Disagree, 3=Somewhat disagree, 4=Somewhat agree,

5=Agree, 6=Strongly agree).

Note that the word “coursework” refers to anything that you do in the online mathematics course, including assignments, activities, readings, etc.

51. [___] I feel motivated to explore content related questions. **(CP)**
52. [___] I utilize a variety of information sources to explore problems posed in this course. **(CP)**
53. [___] Brainstorming and finding relevant information helps me resolve content related questions. **(CP)**

54. [___] Online discussions are valuable in helping me appreciate different perspectives. **(CP)**
55. [___] Combining new information helps me answer questions raised in course activities. **(CP)**
56. [___] Learning activities help me construct explanations/solutions. **(CP)**
57. [___] Reflection on course content and discussions help me understand fundamental concepts in this class. **(CP)**
58. [___] I can describe ways to test and apply the knowledge created in this course. **(CP)**
59. [___] I have developed solutions to course problems that can be applied in practice. **(CP)**
60. [___] I can apply the knowledge created in this course to my work or other non-class related activities. **(CP)**

<Start of **Demographic** *statements - students did not see this comment and it is provided here to help the reader of Appendix B.>*

PART 7 of 7

Do you consider yourself to be trans* or transgender? [___] Yes [___] No [___] Unsure or undecided [___] Decline to answer

What is your gender identity? [___] Woman [___] Man [___] Nonbinary (gender identity which does not fit the male/female binary) or genderfluid (gender identity that varies over time) [___] Unsure or undecided [___] Another identity (please specify) [______________________________] [___] Decline to answer

Do you identify as an ethnic or racial minority? [___] Yes [___] No [___] Decline to answer

In what year were you born? [___] Birth Year: [______] [___] Decline to answer

What is your current relationship status? [___] Married [___] Partnered [___] Single, never married [___] Divorced/Widowed [___] Decline to answer

Are you financially independent from your parents for financial aid purposes? [___] Yes [___] No [___] Decline to answer

Are you responsible for any dependents (other than your spouse)? [___] Yes [___] No [___] Decline to answer

Do you have a High School Diploma? [___] Yes [___] No [___] I have a GED (or equivalent) [___] Decline to answer

What is your current university enrollment status? [___] Full-time student [___] Part-time student [___] Decline to answer

How many hours per week do you USUALLY work at your job? [___] Full-time (at least 35 hours a week on average) [___] Part-time (less than 35 hours a week on average) [___] I am not currently employed

How long has it been (in years) since you took your last mathematics class? Enter -0- if it has been less than 1 year. [___] Enter number of years: [______] [___] Decline to answer

THANK-YOU FOR YOUR PARTICIPATION

Thank you for your time to take the ***Online Mathematics Perceptions and Student Retention*** survey.

The researchers appreciate you taking the time to respond. We will be studying how the online developmental mathematics course learning environment and student motivation play a role in students' decision to persist/drop out of a course and enroll in future mathematics courses. Your responses will help to add understanding to this topic.

If you agree to participate now and change your mind later, you may withdraw at any time by contacting Sam Gedeborg at (801)210-0162 or `sgedeborg@aggiemail.usu.edu` and requesting to be removed from the study. If you choose to withdraw after we have already collected information about you, we will remove your data as long as the request has been made before we remove identifying information (which will be completed in the subsequent semester). If you decide not to participate, the services you receive from your online mathematics course will not be affected in any way.

Confirmation of Survey Completion for $5 Amazon Gift Card:

Please verify your email address: **<insert participant's email address>**

(***Note:*** This email address will not be used for any other purpose than to email your Amazon gift card)

Your confirmation number for completing this survey:

<insert participant's name>

You will receive an email with your gift card within one week upon completion of the survey. If the email address above is incorrect, or it has been more than one week and you have not received your gift card, please email inquiries to sgedeborg@aggiemail.usu.edu.

Appendix C

MUSIC Motivation Inventory Permission

Appendix C: MUSIC® Model of Motivation Inclusion Permission

Initial Request Letter
On Mon, Sep 19, 2016 at 10:01 AM, Samuel Gedeborg

Dr. Jones,

I am a current Ph.D. student studying Mathematics Education in Curriculum and Instruction at Utah State University. I am currently working on a pilot study for a dissertation proposal and possibly dissertation study. I was hoping to use a few of your developed MUSIC Inventory for college students and the professor version. The pilot study will not be going through IRB or for publication purposes and I will only be conducting it with my class of roughly 25 participants. However, through my proposal I hope I can show value of using this Inventory to gather data about student motivation and then compare this with social presence factors, completion rates, etc. If successful in my proposal, I will also use the Inventory throughout my dissertation study as well.

If permitted, I will cite your work throughout my proposal, while collecting data, and throughout future dissertation study if my committee accepts the proposal. I will be following the guidelines you expressed in the User Guide to Assessing the MUSIC Model Components published in June, 2016. This work is completely academic and there are no commercial purposes behind the study.

Thank-you for your time and consideration in this matter.

Best wishes,

Samuel Gedeborg

Ph.D. Student, Curriculum and Instruction

Utah State University

Reply from Author
On Mon, Sep 19, 2016 at 9:37 AM, Brett D. Jones

Hi Sam, Thanks for the message, I'm glad that you're interested in using the MUSIC Inventory. You have my permission to use the MUSIC Inventory for non-commercial uses such as research and teaching. However, you cannot profit from the sale or use of the MUSIC Inventory or the MUSIC Model of Motivation (MUSIC is a registered trademark by Brett D. Jones). If you present or publish your results, simply reference the MUSIC Inventory as part of the User Guide (available at www.theMUSICmodel.com) as is explained in the User Guide.

It sounds like you want to use it exactly as it is intended to be used, so that is great! You may also want to use some of the open-ended items in the User Guide (or others you create) to collect some qualitative data related to each of the MUSIC components.

Also, I don't know if it is helpful to you or not, but I recently published a book about using the MUSIC model to motivate students:

`http://tinyurl.com/motivatingstudentsbydesign1e`

Please let me know if you have any further questions. Thank you for your interest and good luck in your study! Definitely let me know how it goes as things proceed.

Brett

Permission Request for Content Use in Dissertation
On Thu, Oct 24, 2019 at 10:24 AM, Sam Gedeborg

Dr. Jones,

I will be defending my dissertation on October 30th, 2019. The study heavily uses the factors from the MUSIC Model of Motivation as predictors of course persistence, completion and retention. Your work is foundational to my study and conceptual framework and thank you so much for your time and efforts on improving education. Appendix C includes the letter you wrote in 2016 granting permission for non-commercial and non-profit use of the inventory.

Upon successful defense, I will begin the process of publishing my dissertation through Utah State University and will also seek for other academic (non-profit) publications. In writing the paper, I found the table in your 'User Guide for Assessing the Components of the MUSIC Model of Motivation' helpful to concisely explain the motivational factors and definitions. This table is located on page 27 (PDF page 43) with the current attribution (please see attached document). Note: this document is still in draft form until approved by my dissertation committee.

However, in order to respect the copyright nature of your work I would like to say that this table is reprinted with permission from the author and modify Appendix C to reflect this permission. If you wish to have me represent the table any differently I would be happy to make modifications to reflect your work appropriately. If you wish for me to not include this table, I would be happy to fulfill your wishes and will remove it from my dissertation before publication and make sure to not include it in other academic articles I will publish.

Thank you for your consideration and please let me know if you have any other questions or concerns for me.

Best wishes,

Samuel Gedeborg

Ph.D. Candidate, Curriculum and Instruction

Utah State University

Reply from Author - Content Use
On Thu, Oct 24, 2019 at 8:35 PM, Brett D. Jones

Thank you for the update, good luck in your final dissertation defense! You have my permission to use Table 1 from page 5 of this source: Jones, B. D. (2017). User guide for assessing the components of the MUSIC® Model of Motivation. Retrieved from `http://www.theMUSICmodel.com`.

To do so, please include the following statement as a note at the bottom of the table:

From the "User Guide for Assessing the Components of the MUSIC® Model of Motivation," by B. D. Jones, 2017, p. 5, available at www.theMUSICmodel.com. Copyright 2017 by Brett D. Jones.

In your text, to reference the MUSIC® Model of Motivation, you can cite Jones (2009, 2018). To reference the MUSIC® Model of Academic Motivation Inventory, you can cite Jones (2017).

Jones, B. D. (2009). Motivating students to engage in learning: The MUSIC Model of Academic Motivation. International Journal of Teaching and Learning in Higher Education, 21(2), 272-285. Jones, B. D. (2018). Motivating students by design: Practical strategies for professors (2nd ed.). Charleston, SC: CreateSpace. Jones, B. D. (2017). User guide for assessing the components of the MUSIC® Model of Motivation. Retrieved from `http://www.theMUSICmodel.com`

I typically use the trademark sign after the word "MUSIC" only when I refer to the full title of the MUSIC® Model of Motivation or the MUSIC® Model of Academic Motivation Inventory, and then abbreviate it as the "MUSIC model" and the "MUSIC Inventory" (although in one paper we used MMI for MUSIC Model Inventory); you can abbreviate it any way you wish.

Thank you and let me know if you have any other questions.

Brett Jones

Appendix D

Institution Letter of Support Request

Appendix D: Institution Letter of Support Request

Hello **Developmental Department Head**:

My name is Sam Gedeborg, and I am a Ph.D. student at Utah State University (USU). For my dissertation I will be conducting an IRB-approved study investigating student perceptions of the online learning environment and their motivation in online developmental mathematics with the relationship to course persistence and retention.

I am looking for *study participants* in *online developmental mathematics courses* in the *Utah System of Higher Education* (USHE) to participate in this study. Students will be requested to take a 60-item survey which can be previewed here: Preview of Developmental Mathematics Online Course Perceptions Survey. This survey should take about 10-15 minutes for your students to complete in the third or fourth week into the course. I will then also contact the <**insert university's name**>'s registrar office to request consenting participants' course completion and enrollment data in the subsequent semester.

At this time, I am requesting a *letter of support* from those institutions willing to participate in the study to be included in the IRB submission at USU. Once I have received IRB approval at USU, I will then work with you and <**insert university's name**>'s IRB to make sure everything is in compliance at your university for this study.

What will you need to do during the study? I will work with you to identify the online developmental mathematics courses at your institution that meet the criteria of the study and create unique survey links for each course for the participants in the study. I will then give you the unique survey link and distribution instructions to share with your instructors teaching those courses. With your permission, I will also email the instructors to verify participation and provide brief reminders on the deadlines for survey collection.

Upon completion of the data collection I will be sharing all results and findings with relevant departments at participating institutions.

If you have any further questions for me about the study, please let me know. If you are not responsible for the Developmental Mathematics at your University, would you kindly reply to this email to inform me and tell me who is responsible (if known).

Thank you in advance for your assistance!

Best wishes,

Samuel Gedeborg

Ph.D. Student, Curriculum and Instruction

Utah State University

Appendix E

Institution Recruitment Email

Appendix E: Institution Recruitment Email

Dear **Developmental Department Head**,

I hope your Fall 2018 semester has started great!

My name is Sam Gedeborg and I am performing my dissertation study at USHE institutions with the title of_: Relationships Between the Learning Environment, Student Motivation, and Course Persistence and Retention: Students' Perceptions of Online Developmental Mathematics Coursework_ (Utah State University IRB General - #9510). The researchers have contacted the IRB office at <**insert university's name**> and they are aware of this study and are allowing the researchers to recruit participants at your institution in accordance with the approved USU IRB.

I will be reaching out to instructors who teach online developmental mathematics courses at <**insert university's name**> and inviting them to participate in this study by having their students (1) take a survey measuring their perceptions of their online course and (2) agree to have researchers gain access to their grades and enrollment data for course persistence and retention data.

We are hoping to share findings of this study with departments at all participating institutions. The IRB office at Utah State University, who has approved this study (see approval letter attached), has requested that the researchers contact the instructors directly so that there is no perception of coercion on the part of the departments. Also, the data collected will be reported in the aggregate format without being a comparative study of different institutions/courses. This study is not a measure of the performance of an online instructor and is focused on measuring students' perceptions of their online developmental mathematics courses and how these perceptions relate to course persistence and retention. You can read the recruitment letter I will be sending to your instructors, and the letter that I will request participating instructors to share with their students (see attached).

Feel free to let instructors know that I will be reaching out to them directly with this request later this week if you wish. If you prefer that I do not recruit your instructors to participate in this study, please let me know by replying to this email and we will be sure not to contact your instructors.

Here is the seven-step process I will be conducting for this research study:

1. Confirming identified online developmental mathematics courses with Department Chair.
2. Recruiting voluntary participants from faculty.

3. Having the faculty distribute student recruitment information to their classes.
4. Students who consent to the study will fill out the following survey (and give agreement to have researchers receive their grade/enrollment information):

- You can preview the survey here if you wish: `https://usu.co1.qualtrics.com/jfe/preview/SV_ahjIxfbNX6RISGh?Q_SurveyVersionID=current&Q_CHL=preview`

5. Contact the Registrar's Office to collect data from student participants.
6. Combine data sources and remove identifying information.
7. Analyze and report aggregate information to respect privacy and confidentiality.

At this time, I am confirming with you the identified online developmental mathematics courses through publicly available scheduling data at your institution. If there are courses/instructors that I have forgotten on this list, please let me know so I can add them to my recruitment data sheet:

<**course name**> | <**instructor name**> | <**instructor email**> | <**enrollment**>

Thank you for all your work and be sure to let me know if you have any further questions/concerns that I can help address.

Best wishes,

Samuel Gedeborg

Ph.D. Student, Curriculum and Instruction

Utah State University

Appendix F

Instructor Distribution Instructions

Appendix F: Instructor Distribution Instructions

Dear **Online Developmental Mathematics Instructor**:

My name is Samuel Gedeborg, and I am a Ph.D. student at Utah State University (USU). For my dissertation I am conducting an IRB-approved study #9510 investigating student perceptions of the online learning environment and their motivation in online developmental mathematics and the relationship to course persistence and retention in future mathematics enrollment. Your university has graciously agreed to allow me to invite your class to participate in this research study. While there is minimal amount of work required on your part, your participation is completely voluntary and there will be no work repercussions for not participating in this study.

The following course(s) you teach have been identified as one that meets the criteria for this study:

<**insert course name here**>

Students will be requested to take a 60-item survey which can be previewed here: `https://usu.co1.qualtrics.com/jfe/preview/SV_ahjIxfbNX6RISGh?Q_CHL=preview`. This survey should take about 10 - 15 minutes for your students to complete. If you agree to participate in this study I will have you send an email or announcement to your students requesting their support throughout the third and fourth weeks of the Fall 2018 semester.

When you reply to this email informing me of your willingness to participate, please let me know if you (1) wish to make this survey an assignment/extra credit and I will provide a unique receipt for each student or (2) that you do not wish this to be an assignment/extra credit and then I will give the option in your survey link for participants to receive an equivalent compensation of a $5 Amazon gift card.

For your information, I will also be contacting the <**insert university's name**>'s registrar office to request consenting participants' course completion and continuing enrollment data during the following semester from the survey data collection. It will be important that you report the Unofficial Withdraw dates as accurate as you can according to the <**insert university's name**>'s Policy and federal financial aid requirements. If a student stops participating in a course (but does not officially withdraw) before the last day to withdraw, he/she should receive a "UW" with the date of their last activity in the class. While this grade is used to determine eligibility for financial aid, this grade will also be used in the study to measure course persistence.

Please note: All results and findings will be shared generally and in aggregate form with relevant departments at participating institutions and these results will not be tracked to you or your course. As with most research, there is a minimal risk of loss of confidentiality and loss of privacy, but the researchers will do everything in their power to protect both your confidentiality and privacy. This study is not a measure of your personal performance as an online instructor and is focused on measuring students' perceptions of their online developmental mathematics courses and how it relates to course persistence and retention.

Thank you in advance for your support!

Best wishes,

Samuel Gedeborg

Ph.D. Student, Curriculum and Instruction

Utah State University

Appendix G

Online Student Recruitment Letter

Appendix G: Online Student Recruitment Letter

Hello **Online Mathematics Student**! You are receiving this request because you are enrolled in <**insert course name**> at <**insert institution name**> with <**insert instructor's name**>.

My name is Samuel Gedeborg, and I am a Ph.D. student at Utah State University (USU). For my dissertation I am conducting an IRB-approved study #9510 investigating student perceptions of online mathematics courses. As part of this study, I am asking you to explore your perceptions of your current online mathematics course.

This survey should take about 10 - 15 minutes. To show appreciation for your time to take this survey, your teacher has agreed to make this an extra credit assignment and you will receive a confirmation code (regardless if you decide to participate in this study or not).

You are free to withdraw from the study at any time. If you have any questions about participation, please feel free to contact me via text/voice at (801) 210-0162 or through email at `sgedeborg@aggiemail.usu.edu`.

Proceed to the survey by clicking on the survey link below:

<**unique survey code to identify class/instructor/institution**>

The survey must be completed by September 14, 2018.

Thank you in advance for your assistance!

Best wishes,

Samuel Gedeborg

Ph.D. Student, Curriculum and Instruction

Utah State University

Appendix H

Online Student Last Call Letter

Appendix H: Online Student Last Call Letter

Dear **online math student** in <**insert instructor's name**>'s <**insert course name**> course,

There are still a couple days left to participate in a study researching online mathematics courses. You have 48 hours to complete this survey from when this message was sent out.

Your participation will help researchers and instructors better serve online mathematics students. The survey will take about 10 minutes to complete. Upon completion, a $5 Amazon Gift Card will be emailed to those who participate. To join the study, please click on the following link:

Online Mathematics Perceptions and Retention Study

<**insert hyperlink to unique survey**>

For questions about gift cards, or details about the study, please contact Samuel Gedeborg at `sgedeborg@aggiemail.usu.edu`.

Best wishes,

Samuel Gedeborg

Ph.D. Student, Curriculum and Instruction

Utah State University

Appendix I

Registrar's Office Data Request

Appendix I: Registrar's Office Data Request

Dear <**insert university's name**>'s Office:

My name is Sam Gedeborg and I am a PhD candidate student at Utah State University. As part of my study and analysis I will need some Registrar Data (which either you can provide or direct me to who can provide me the needed information at your Institution – such as the Institutional Research area).

As part of the required data for my accepted IRB study, I need the following:

> **Registrar Data:** _ Once the Fall 2018 semester has concluded, the researcher will reach out to the Registrar's Office at the student's institution who have given consent. A request for (a) student's completed grade -or- if they withdrew (and date) -or- if they unofficially withdrew (and date) and (b) did the student register for a mathematics class in the subsequent semester (Y or N). The researchers will also request from the registrar's office the public record of Grade Distribution data (free of FERPA protected data) for the online developmental mathematics courses to help analyze and measure course persistence._

My study was initially approved at Utah State University with an **IRB protocol number #9510**. The survey was conducted with the students during the Fall 2018 semester and each student signed the following agreement to share FERPA protected data as part of that survey:

> *Please sign below showing that you agree to have the researchers contact the Registrar's Office to release (1) the grade/outcome you received in the online mathematics course and (2) your enrollment in a mathematics course for the subsequent semester. These data will be used to measure course persistence and retention and will be highly protected as outlined in the consent form.*

The attached Excel Document contains a unique ID which represents the signature provided by the student and is stored on Qualtrics.

I need the following information from <**insert university's name**>:

FIRST:

The attached Spreadsheet completed with the three missing values. I requested student names and ID numbers to give you multiple options to correctly identify participating students. Once I tie your submitted information in with my survey data, I will remove all identifying information of FERPA protected data:

1. *FinalGrade:*

   This will be the grade in the Mathematics course the student earned for the Fall 2018 semester.

2. *LastAttendedDate*

   If the student withdrew (or had an unofficial withdraw) this is the "last date attended" as reported by the University Instructor.

3. *EnrolledSpring2019*

   Did that student enroll in a Mathematics course for the Spring 2019 semester? This can be a **Y** for (Yes) or a **N** for (No).

SECOND:

I am requesting Grade Distribution Data by percent and/or letter grade for each of the following courses for the Fall 2018 semester. Please make sure that these documents are FERPA compliant.

Course Grade Distributions Requested from

<insert course name> <insert instructor's name>

<insert course name> <insert instructor's name>

I appreciate your timeliness with this request and if you have any further questions and/or concerns, please let me know. If this is not something you can provide, would you mind directing me to the person to whom I can make this request?

Best wishes,

Samuel Gedeborg

Ph.D. Student, Curriculum and Instruction

Utah State University

Appendix J

Comprehensive Outline of All Data Analysis Procedures

Appendix J: Comprehensive Outline of All Data Analysis Procedures

Preparation

Software Used

All data analysis performed in this study was done on a Macbook Pro running macOS Catalina Version 10.15.3 with the RStudio Version 1.2.5033 "Elderflower" (fba733f0). The formatting of the file was developed by the author with support provided by the Utah State University Statistical Consulting Studio. (Barrett & Schwartz, 2019; R Core Team, 2019)

Data Dictionary

M_Subscore (continuous): Mean of eMpowerment survey items (scaled 1-6).

U_Subscore (continuous): Mean of Usefulness survey items (scaled 1-6).

S_Subscore (continuous): Mean of Success survey items (scaled 1-6).

I_Subscore (continuous): Mean of Interest survey items (scaled 1-6).

C_Subscore (continuous): Mean of Caring survey items (scaled 1-6).

TeachingPresence (continuous): Mean of Teaching Presence survey items (scaled 1-6).

SocialPresence (continuous): Mean of Social Presence survey items (scaled 1-6).

Cognitive Presence (continuous): Mean of Cognitive Presence survey items (scaled 1-6).

DaysPersisted (ordinal): The number of days a student stayed in class until they dropped, withdrew, unofficially withdrew, or failed to earn a 'C-' or higher in the class.

notCompleted (binary): This variable contained a '1' if the student withdrew, unofficially withdrew, or failed to earn a 'C-' or higher in the class and a '0' otherwise.

EnrolledSpring2019 (binary): This variable contained a '1' if the student enrolled in a developmental mathematics class in the Spring 2019 semester and a '0' if they did not.

Tertile Values

Tertile values as described in Chapter 3 under data preparation (used for Kaplan-Meier Plots and Log-rank Test):

M_Subscore_Tertile (categorical): An eMpowerment score of 'High', 'Med', and 'Low' to represent the 3 tertiles.

U_Subscore_Tertile (categorical): A Usefulness score of 'High', 'Med', and 'Low' to represent the 3 tertiles.

S_Subscore_Tertile (categorical): A Success score of 'High', 'Med', and 'Low' to represent the 3 tertiles.

I_Subscore_Tertile (categorical): An Interest score of 'High', 'Med', and 'Low' to represent the 3 tertiles.

C_Subscore_Tertile (categorical): A Caring score of 'High', 'Med', and 'Low' to represent the 3 tertiles.

TP_Subscore_Tertile (categorical): A Teaching Presence score of 'High', 'Med', and 'Low' to represent the 3 tertiles.

SP_Subscore_Tertile (categorical): A Social Presence score of 'High', 'Med', and 'Low' to represent the 3 tertiles.

CP_Subscore_Tertile (categorical): A Cognitive Presence score of 'High', 'Med', and 'Low' to represent the 3 tertiles.

Demographic Values

StudentID (categorical): Unique identifier to this dataset for each student.

SchoolID (categorical): The public university in Utah the student took the course in - part of the Utah System of Higher Education (USHE).

CourseID (categorical): The course section of online developmental mathematics the student enrolled in.

Load Packages

```
library(apaTables) # Create APA Style Tables
library(broom) # Convert Statistical Analysis
library(car) # Companion to Applied Regression
library(corrplot) # Visualization of a Cor Matrix
```

```
library(coxme) # Mixed Effects Cox Models
library(dplyr) # A Grammar of Dta Manipulation
library(furniture) # Furniture for Quantitative Scientists
library(ggfortify) # Data Visual Tools for Statistical Analysis
library(gridExtra) # place ggplots togeter as one plot
library(haven) # Import and Export 'SPSS', 'Stata' and 'SAS' Files
library(HLMdiag) # Diagnostic Tools for nlme & lmer4
library(kableExtra) # Construct Complex Table with 'kable'
library(knitr) # Dynamic Report Generation in R
library(lavaan) # Latent Variable Analysis
library(lme4) # Linear, generalized linear, & nonlinear mixed models
library(lmerTest) # Tests on lmer objects
library(nlme) # non-linear mixed-effects models
library(magrittr) # A Forward-Pipe Ope*rator for R
library(multilevel) # Multilevel Functions
library(optimx) # Different optimizers to solve mlm's
library(pander) # An R 'Pandoc' Writer
library(performance) # Regression Models Performance
library(pscl) # Political Science Computationl Laboratory
library(psych) # Procedures for Psychological and Personality Research
library(ranger) # A Fast Implementation of Random Forests
library(readxl) # Read Excel Files
library(sjPlot) # Data Visualization for Statistics in
library(sjstats) # Functions for Common Statistical Computations
library(stargazer) # Well-Formed Regression/Summary Statistics Tables
library(survival) # Survival Analysis
library(survminer) # Drawing Survival Curves using 'ggplot2'
library(texreg) # Conversion of R Regresssion Output
library(tidyverse) # Easily Install and Load the 'Tidyverse'
library(xtable) # Export Tables to LaTex or HTML
```

Import Data

```
data_raw <- readxl::read_excel("Gedeborg_Dissertation_DataSet.xlsx")
```

Wrangle Data

```
data_clean <- data_raw %>%
  dplyr::mutate_if(is.character, as.factor) %>%
  dplyr::select(StudentID, CourseID, SchoolID,
                Gender, EthnicMinority,
                Age, MaritalStatus, Employment,
                CourseID, notCompleted,
```

```
              DaysPersisted, EnrolledSpring2019,
              M_Subscore, M_Subscore_Tertile,
              U_Subscore, U_Subscore_Tertile,
              S_Subscore, S_Subscore_Tertile,
              I_Subscore, I_Subscore_Tertile,
              C_Subscore, C_Subscore_Tertile,
              TP_Subscore, TP_Subscore_Tertile,
              SP_Subscore, SP_Subscore_Tertile,
              CP_Subscore, CP_Subscore_Tertile)

data_corr <- data_raw %>%
  dplyr::mutate_if(is.character, as.factor) %>%
  dplyr::select(CourseID,
              M_Subscore, U_Subscore, S_Subscore,
              I_Subscore, C_Subscore, TP_Subscore,
              SP_Subscore, CP_Subscore)
```

Factor Analysis

Each of the eight factor scores of motivation and the learning environment were generated from survey items. A confirmatory factor analysis using the lavaan R package (Rosseel, 2019) was performed on the model to determine if it was a good fit. In order to take nesting into consideration (students within eight different universities winthin different courses), the analysis was clustered using the unique school and course variables (Pornprasertmanit et al., 2014). The model chi-square, RMSEA, CFI, SRMR are reported and discussed. The researcher next calculated the Cronbach alpha for each of the factors in order to determine internal consistency and reliability. A Cronbach alpha value of .7 or higher is considered to be acceptable in social science research. The researcher used the psych package in R to calculate the alpha coefficient of reliability to measure internal consistency. A listwise deletion was used for the empty spaces in calculating the Cronbach alpha.

eMpowerment Cronbach Alpha

```
mainModel <- '
     eMpowerment =~ M_2 + M_8 + M_12 + M_17 + M_26
     Usefulness =~ U_3 + U_5 + U_19 + U_21 + U_23
     Success =~ S_7 + S_10 + S_14 + S_18
     Interest =~ I_1 + I_6 + I_9 + I_11 + I_13 + I_15
     Care =~ C_4 + C_16 + C_20 + C_22 + C_24 + C_25
     TeachingPresence =~ TP_27 + TP_28 + TP_29 + TP_30 +
          TP_31 + TP_32 + TP_33 + TP_34 + TP_35 + TP_36 +
          TP_37 + TP_38 + TP_39
     SocialPresence =~ SP_40 + SP_41 + SP_42 + SP_43 +
          SP_44 + SP_45 + SP_46 + SP_47 + SP_48
     CognitivePresence =~ CP_49 + CP_50 + CP_51 + CP_52 +
          CP_53 + CP_54 + CP_55 + CP_56 + CP_57 + CP_58 +
          CP_59 + CP_60
'

fit <- cfa(model = mainModel, data = data_raw, cluster="SchoolID")
summary(fit, fit.measures = TRUE)

## lavaan 0.6-5 ended normally after 114 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of free parameters                        208
##
##                                                   Used       Total
```

```
##   Number of observations                           303         330
##   Number of clusters [SchoolID]                      8
##
## Model Test User Model:
##                                               Standard      Robust
##   Test Statistic                              4840.508    4322.984
##   Degrees of freedom                              1682        1682
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  1.120
##     for the Yuan-Bentler correction (Mplus variant)
##
## Model Test Baseline Model:
##
##   Test statistic                             17503.488   15556.698
##   Degrees of freedom                              1770        1770
##   P-value                                        0.000       0.000
##   Scaling correction factor                                  1.125
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.799       0.808
##   Tucker-Lewis Index (TLI)                       0.789       0.798
##
##   Robust Comparative Fit Index (CFI)                         0.809
##   Robust Tucker-Lewis Index (TLI)                            0.799
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -20832.881  -20832.881
##   Scaling correction factor                                  1.748
##       for the MLR correction
##   Loglikelihood unrestricted model (H1)     -18412.627  -18412.627
##   Scaling correction factor                                  1.189
##       for the MLR correction
##
##   Akaike (AIC)                               42081.762   42081.762
##   Bayesian (BIC)                             42854.218   42854.218
##   Sample-size adjusted Bayesian (BIC)        42194.551   42194.551
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.079       0.072
##   90 Percent confidence interval - lower         0.076       0.069
```

```
##   90 Percent confidence interval - upper         0.081       0.074
##   P-value RMSEA <= 0.05                          0.000       0.000
##
##   Robust RMSEA                                               0.076
##   90 Percent confidence interval - lower                     0.073
##   90 Percent confidence interval - upper                     0.079
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.067       0.067
##
## Parameter Estimates:
##
##   Information                                  Observed
##   Observed information based on                 Hessian
##   Standard errors                        Robust.cluster
##
## Latent Variables:
##                        Estimate  Std.Err  z-value  P(>|z|)
##   eMpowerment =~
##     M_2                   1.000
##     M_8                   1.108    0.060   18.507    0.000
##     M_12                  1.072    0.124    8.659    0.000
##     M_17                  1.048    0.102   10.313    0.000
##     M_26                  1.204    0.120   10.046    0.000
##   Usefulness =~
##     U_3                   1.000
##     U_5                   1.094    0.043   25.494    0.000
##     U_19                  1.670    0.191    8.737    0.000
##     U_21                  1.398    0.120   11.616    0.000
##     U_23                  1.544    0.151   10.248    0.000
##   Success =~
##     S_7                   1.000
##     S_10                  0.956    0.037   25.681    0.000
##     S_14                  0.858    0.077   11.086    0.000
##     S_18                  0.941    0.031   30.849    0.000
##   Interest =~
##     I_1                   1.000
##     I_6                   1.162    0.092   12.585    0.000
##     I_9                   1.190    0.091   13.025    0.000
##     I_11                  1.248    0.096   12.983    0.000
##     I_13                  1.205    0.054   22.485    0.000
##     I_15                  1.269    0.137    9.269    0.000
```

```
##   Care =~
##     C_4                1.000
##     C_16               1.043    0.099   10.487    0.000
##     C_20               1.151    0.072   16.065    0.000
##     C_22               0.732    0.070   10.488    0.000
##     C_24               0.794    0.036   22.240    0.000
##     C_25               1.170    0.082   14.319    0.000
##   TeachingPresence =~
##     TP_27              1.000
##     TP_28              1.201    0.158    7.621    0.000
##     TP_29              1.175    0.194    6.064    0.000
##     TP_30              0.857    0.112    7.624    0.000
##     TP_31              1.914    0.227    8.429    0.000
##     TP_32              1.906    0.222    8.583    0.000
##     TP_33              2.129    0.275    7.749    0.000
##     TP_34              2.015    0.267    7.560    0.000
##     TP_35              2.111    0.245    8.623    0.000
##     TP_36              1.789    0.248    7.201    0.000
##     TP_37              2.030    0.247    8.213    0.000
##     TP_38              1.666    0.220    7.568    0.000
##     TP_39              1.203    0.193    6.246    0.000
##   SocialPresence =~
##     SP_40              1.000
##     SP_41              1.033    0.055   18.782    0.000
##     SP_42              1.001    0.109    9.161    0.000
##     SP_43              0.934    0.147    6.342    0.000
##     SP_44              1.092    0.137    7.996    0.000
##     SP_45              1.205    0.148    8.128    0.000
##     SP_46              1.152    0.113   10.153    0.000
##     SP_47              1.103    0.092   12.058    0.000
##     SP_48              1.206    0.078   15.421    0.000
##   CognitivePresence =~
##     CP_49              1.000
##     CP_50              0.999    0.068   14.664    0.000
##     CP_51              1.156    0.051   22.514    0.000
##     CP_52              0.986    0.044   22.349    0.000
##     CP_53              0.862    0.074   11.609    0.000
##     CP_54              0.945    0.090   10.478    0.000
##     CP_55              0.851    0.050   17.077    0.000
##     CP_56              0.839    0.107    7.804    0.000
##     CP_57              0.835    0.053   15.758    0.000
##     CP_58              0.927    0.045   20.780    0.000
##     CP_59              0.870    0.098    8.873    0.000
```

```
##     CP_60                  1.046    0.060   17.354    0.000
##
## Covariances:
##                        Estimate  Std.Err  z-value  P(>|z|)
##    eMpowerment ~~
##      Usefulness           0.340    0.056    6.119    0.000
##      Success              0.491    0.138    3.554    0.000
##      Interest             0.449    0.083    5.425    0.000
##      Care                 0.277    0.063    4.389    0.000
##      TeachingPresnc       0.213    0.049    4.306    0.000
##      SocialPresence       0.328    0.069    4.763    0.000
##      CognitivePrsnc       0.441    0.054    8.171    0.000
##    Usefulness ~~
##      Success              0.348    0.064    5.425    0.000
##      Interest             0.410    0.083    4.936    0.000
##      Care                 0.183    0.048    3.815    0.000
##      TeachingPresnc       0.166    0.062    2.667    0.008
##      SocialPresence       0.303    0.087    3.498    0.000
##      CognitivePrsnc       0.526    0.107    4.927    0.000
##    Success ~~
##      Interest             0.442    0.053    8.402    0.000
##      Care                 0.293    0.049    5.942    0.000
##      TeachingPresnc       0.201    0.054    3.686    0.000
##      SocialPresence       0.306    0.071    4.309    0.000
##      CognitivePrsnc       0.455    0.081    5.646    0.000
##    Interest ~~
##      Care                 0.289    0.039    7.460    0.000
##      TeachingPresnc       0.253    0.041    6.246    0.000
##      SocialPresence       0.390    0.060    6.458    0.000
##      CognitivePrsnc       0.574    0.073    7.912    0.000
##    Care ~~
##      TeachingPresnc       0.223    0.042    5.358    0.000
##      SocialPresence       0.223    0.037    6.064    0.000
##      CognitivePrsnc       0.308    0.027   11.197    0.000
##    TeachingPresence ~~
##      SocialPresence       0.219    0.055    3.950    0.000
##      CognitivePrsnc       0.300    0.047    6.325    0.000
##    SocialPresence ~~
##      CognitivePrsnc       0.592    0.120    4.922    0.000
##
## Intercepts:
##                     Estimate  Std.Err  z-value  P(>|z|)
##     .M_2               5.168    0.078   65.935    0.000
```

```
##    .M_8                  5.122    0.136   37.584    0.000
##    .M_12                 4.845    0.103   46.830    0.000
##    .M_17                 4.904    0.075   65.075    0.000
##    .M_26                 4.759    0.091   52.444    0.000
##    .U_3                  4.825    0.082   58.538    0.000
##    .U_5                  4.917    0.063   78.049    0.000
##    .U_19                 4.254    0.100   42.491    0.000
##    .U_21                 4.594    0.080   57.099    0.000
##    .U_23                 4.528    0.079   57.562    0.000
##    .S_7                  5.036    0.093   54.315    0.000
##    .S_10                 5.086    0.103   49.201    0.000
##    .S_14                 5.135    0.090   56.967    0.000
##    .S_18                 5.053    0.089   56.946    0.000
##    .I_1                  4.710    0.124   38.043    0.000
##    .I_6                  4.498    0.147   30.621    0.000
##    .I_9                  4.594    0.155   29.694    0.000
##    .I_11                 4.475    0.139   32.133    0.000
##    .I_13                 4.459    0.183   24.337    0.000
##    .I_15                 4.149    0.213   19.440    0.000
##    .C_4                  5.419    0.041  133.100    0.000
##    .C_16                 5.409    0.042  130.293    0.000
##    .C_20                 5.191    0.083   62.773    0.000
##    .C_22                 5.508    0.048  113.751    0.000
##    .C_24                 5.512    0.060   91.670    0.000
##    .C_25                 5.083    0.053   95.725    0.000
##    .TP_27                5.271    0.068   77.119    0.000
##    .TP_28                5.287    0.047  112.950    0.000
##    .TP_29                5.261    0.072   73.292    0.000
##    .TP_30                5.419    0.058   92.771    0.000
##    .TP_31                4.752    0.062   76.743    0.000
##    .TP_32                4.828    0.105   46.158    0.000
##    .TP_33                4.739    0.115   41.126    0.000
##    .TP_34                4.845    0.093   52.349    0.000
##    .TP_35                4.660    0.099   46.897    0.000
##    .TP_36                4.752    0.140   33.886    0.000
##    .TP_37                4.719    0.145   32.460    0.000
##    .TP_38                4.624    0.127   36.487    0.000
##    .TP_39                5.158    0.087   59.287    0.000
##    .SP_40                3.904    0.154   25.403    0.000
##    .SP_41                3.561    0.180   19.813    0.000
##    .SP_42                3.997    0.111   35.980    0.000
##    .SP_43                4.667    0.064   72.762    0.000
##    .SP_44                4.637    0.085   54.465    0.000
```

```
##    .SP_45              4.488    0.109   41.295    0.000
##    .SP_46              4.426    0.046   97.059    0.000
##    .SP_47              4.300    0.116   36.962    0.000
##    .SP_48              4.116    0.092   44.934    0.000
##    .CP_49              4.228    0.137   30.859    0.000
##    .CP_50              4.297    0.092   46.724    0.000
##    .CP_51              4.389    0.091   48.088    0.000
##    .CP_52              4.663    0.070   66.757    0.000
##    .CP_53              4.799    0.068   70.445    0.000
##    .CP_54              4.271    0.110   38.855    0.000
##    .CP_55              4.743    0.081   58.299    0.000
##    .CP_56              4.835    0.116   41.746    0.000
##    .CP_57              4.726    0.043  110.464    0.000
##    .CP_58              4.601    0.081   57.035    0.000
##    .CP_59              4.660    0.071   65.671    0.000
##    .CP_60              4.479    0.060   74.885    0.000
##     eMpowerment        0.000
##     Usefulness         0.000
##     Success            0.000
##     Interest           0.000
##     Care               0.000
##     TeachingPresnc     0.000
##     SocialPresence     0.000
##     CognitivePrsnc     0.000
##
## Variances:
##                     Estimate  Std.Err  z-value  P(>|z|)
##    .M_2                0.434    0.066    6.581    0.000
##    .M_8                0.487    0.070    6.937    0.000
##    .M_12               0.364    0.074    4.935    0.000
##    .M_17               0.447    0.069    6.454    0.000
##    .M_26               0.413    0.048    8.510    0.000
##    .U_3                0.600    0.054   11.011    0.000
##    .U_5                0.503    0.081    6.194    0.000
##    .U_19               0.365    0.078    4.700    0.000
##    .U_21               0.333    0.068    4.890    0.000
##    .U_23               0.304    0.031    9.784    0.000
##    .S_7                0.212    0.025    8.608    0.000
##    .S_10               0.198    0.027    7.424    0.000
##    .S_14               0.383    0.048    8.009    0.000
##    .S_18               0.269    0.042    6.449    0.000
##    .I_1                0.416    0.092    4.503    0.000
##    .I_6                0.421    0.052    8.100    0.000
```

```
##    .I_9                 0.516    0.078    6.624    0.000
##    .I_11                0.305    0.032    9.437    0.000
##    .I_13                0.771    0.086    8.956    0.000
##    .I_15                0.828    0.129    6.426    0.000
##    .C_4                 0.226    0.028    8.029    0.000
##    .C_16                0.258    0.033    7.926    0.000
##    .C_20                0.339    0.065    5.258    0.000
##    .C_22                0.148    0.028    5.388    0.000
##    .C_24                0.127    0.021    6.171    0.000
##    .C_25                0.297    0.033    8.928    0.000
##    .TP_27               0.444    0.103    4.309    0.000
##    .TP_28               0.383    0.104    3.689    0.000
##    .TP_29               0.430    0.062    6.969    0.000
##    .TP_30               0.409    0.042    9.696    0.000
##    .TP_31               0.341    0.038    8.911    0.000
##    .TP_32               0.258    0.037    6.886    0.000
##    .TP_33               0.273    0.032    8.427    0.000
##    .TP_34               0.240    0.013   17.869    0.000
##    .TP_35               0.400    0.034   11.855    0.000
##    .TP_36               0.527    0.048   10.955    0.000
##    .TP_37               0.423    0.059    7.203    0.000
##    .TP_38               0.700    0.071    9.901    0.000
##    .TP_39               0.574    0.072    7.954    0.000
##    .SP_40               1.513    0.220    6.864    0.000
##    .SP_41               1.269    0.188    6.748    0.000
##    .SP_42               1.289    0.267    4.830    0.000
##    .SP_43               0.695    0.081    8.550    0.000
##    .SP_44               0.489    0.101    4.837    0.000
##    .SP_45               0.452    0.069    6.587    0.000
##    .SP_46               0.545    0.049   11.191    0.000
##    .SP_47               0.546    0.059    9.292    0.000
##    .SP_48               0.711    0.105    6.781    0.000
##    .CP_49               0.735    0.082    8.942    0.000
##    .CP_50               0.585    0.103    5.686    0.000
##    .CP_51               0.537    0.089    6.009    0.000
##    .CP_52               0.629    0.105    5.975    0.000
##    .CP_53               0.503    0.060    8.390    0.000
##    .CP_54               1.098    0.111    9.913    0.000
##    .CP_55               0.398    0.028   14.080    0.000
##    .CP_56               0.409    0.040   10.185    0.000
##    .CP_57               0.469    0.041   11.528    0.000
##    .CP_58               0.523    0.044   11.975    0.000
##    .CP_59               0.515    0.111    4.621    0.000
```

```
##    .CP_60             0.688    0.066   10.383    0.000
##     eMpowerment       0.670    0.208    3.226    0.001
##     Usefulness        0.548    0.111    4.920    0.000
##     Success           0.714    0.112    6.383    0.000
##     Interest          0.621    0.063    9.856    0.000
##     Care              0.374    0.045    8.231    0.000
##     TeachingPresnc    0.215    0.045    4.832    0.000
##     SocialPresence    0.798    0.161    4.952    0.000
##     CognitivePrsnc    0.853    0.097    8.797    0.000
```

```
fit <- cfa(model = mainModel, data = data_raw, cluster="CourseID")
summary(fit, fit.measures = TRUE)
```

```
## lavaan 0.6-5 ended normally after 114 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of free parameters                        208
##
##                                                   Used       Total
##   Number of observations                           303         330
##   Number of clusters [CourseID]                     36
##
## Model Test User Model:
##                                               Standard      Robust
##   Test Statistic                              4840.508    3940.697
##   Degrees of freedom                              1682        1682
##   P-value (Chi-square)                           0.000       0.000
##   Scaling correction factor                                  1.228
##     for the Yuan-Bentler correction (Mplus variant)
##
## Model Test Baseline Model:
##
##   Test statistic                             17503.488   13945.020
##   Degrees of freedom                              1770        1770
##   P-value                                        0.000       0.000
##   Scaling correction factor                                  1.255
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.799       0.814
##   Tucker-Lewis Index (TLI)                       0.789       0.805
##
```

```
##   Robust Comparative Fit Index (CFI)                          0.818
##   Robust Tucker-Lewis Index (TLI)                             0.809
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)          -20832.881  -20832.881
##   Scaling correction factor                                1.701
##       for the MLR correction
##   Loglikelihood unrestricted model (H1)  -18412.627  -18412.627
##   Scaling correction factor                                1.280
##       for the MLR correction
##
##   Akaike (AIC)                            42081.762   42081.762
##   Bayesian (BIC)                          42854.218   42854.218
##   Sample-size adjusted Bayesian (BIC)     42194.551   42194.551
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                       0.079       0.067
##   90 Percent confidence interval - lower      0.076       0.064
##   90 Percent confidence interval - upper      0.081       0.069
##   P-value RMSEA <= 0.05                       0.000       0.000
##
##   Robust RMSEA                                            0.074
##   90 Percent confidence interval - lower                  0.071
##   90 Percent confidence interval - upper                  0.077
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                        0.067       0.067
##
## Parameter Estimates:
##
##   Information                                 Observed
##   Observed information based on                Hessian
##   Standard errors                       Robust.cluster
##
## Latent Variables:
##                       Estimate  Std.Err  z-value  P(>|z|)
##   eMpowerment =~
##     M_2                  1.000
##     M_8                  1.108    0.083   13.392    0.000
##     M_12                 1.072    0.102   10.495    0.000
```

```
##     M_17                 1.048    0.104   10.026    0.000
##     M_26                 1.204    0.134    8.996    0.000
##   Usefulness =~
##     U_3                  1.000
##     U_5                  1.094    0.055   19.882    0.000
##     U_19                 1.670    0.171    9.768    0.000
##     U_21                 1.398    0.115   12.181    0.000
##     U_23                 1.544    0.147   10.530    0.000
##   Success =~
##     S_7                  1.000
##     S_10                 0.956    0.040   24.099    0.000
##     S_14                 0.858    0.062   13.858    0.000
##     S_18                 0.941    0.040   23.825    0.000
##   Interest =~
##     I_1                  1.000
##     I_6                  1.162    0.072   16.087    0.000
##     I_9                  1.190    0.086   13.915    0.000
##     I_11                 1.248    0.078   15.908    0.000
##     I_13                 1.205    0.091   13.215    0.000
##     I_15                 1.269    0.126   10.092    0.000
##   Care =~
##     C_4                  1.000
##     C_16                 1.043    0.061   17.195    0.000
##     C_20                 1.151    0.104   11.080    0.000
##     C_22                 0.732    0.061   12.086    0.000
##     C_24                 0.794    0.050   15.778    0.000
##     C_25                 1.170    0.074   15.734    0.000
##   TeachingPresence =~
##     TP_27                1.000
##     TP_28                1.201    0.119   10.083    0.000
##     TP_29                1.175    0.184    6.395    0.000
##     TP_30                0.857    0.126    6.827    0.000
##     TP_31                1.914    0.260    7.376    0.000
##     TP_32                1.906    0.270    7.067    0.000
##     TP_33                2.129    0.274    7.778    0.000
##     TP_34                2.015    0.269    7.491    0.000
##     TP_35                2.111    0.277    7.626    0.000
##     TP_36                1.789    0.257    6.975    0.000
##     TP_37                2.030    0.296    6.857    0.000
##     TP_38                1.666    0.283    5.885    0.000
##     TP_39                1.203    0.214    5.628    0.000
##   SocialPresence =~
##     SP_40                1.000
```

```
##     SP_41                 1.033    0.086   11.962    0.000
##     SP_42                 1.001    0.107    9.393    0.000
##     SP_43                 0.934    0.129    7.253    0.000
##     SP_44                 1.092    0.159    6.850    0.000
##     SP_45                 1.205    0.162    7.450    0.000
##     SP_46                 1.152    0.124    9.329    0.000
##     SP_47                 1.103    0.089   12.337    0.000
##     SP_48                 1.206    0.080   14.988    0.000
##   CognitivePresence =~
##     CP_49                 1.000
##     CP_50                 0.999    0.049   20.202    0.000
##     CP_51                 1.156    0.060   19.247    0.000
##     CP_52                 0.986    0.075   13.078    0.000
##     CP_53                 0.862    0.081   10.632    0.000
##     CP_54                 0.945    0.098    9.680    0.000
##     CP_55                 0.851    0.069   12.264    0.000
##     CP_56                 0.839    0.078   10.695    0.000
##     CP_57                 0.835    0.060   13.971    0.000
##     CP_58                 0.927    0.074   12.549    0.000
##     CP_59                 0.870    0.083   10.476    0.000
##     CP_60                 1.046    0.074   14.116    0.000
##
## Covariances:
##                       Estimate  Std.Err  z-value  P(>|z|)
##   eMpowerment ~~
##     Usefulness           0.340    0.069    4.897    0.000
##     Success              0.491    0.113    4.334    0.000
##     Interest             0.449    0.097    4.604    0.000
##     Care                 0.277    0.064    4.355    0.000
##     TeachingPresnc       0.213    0.046    4.583    0.000
##     SocialPresence       0.328    0.058    5.610    0.000
##     CognitivePrsnc       0.441    0.060    7.335    0.000
##   Usefulness ~~
##     Success              0.348    0.053    6.514    0.000
##     Interest             0.410    0.069    5.904    0.000
##     Care                 0.183    0.035    5.310    0.000
##     TeachingPresnc       0.166    0.033    5.059    0.000
##     SocialPresence       0.303    0.060    5.020    0.000
##     CognitivePrsnc       0.526    0.070    7.493    0.000
##   Success ~~
##     Interest             0.442    0.061    7.290    0.000
##     Care                 0.293    0.060    4.920    0.000
##     TeachingPresnc       0.201    0.037    5.397    0.000
```

```
##     SocialPresence       0.306    0.071    4.302    0.000
##     CognitivePrsnc       0.455    0.070    6.477    0.000
##   Interest ~~
##     Care                 0.289    0.057    5.097    0.000
##     TeachingPresnc       0.253    0.034    7.342    0.000
##     SocialPresence       0.390    0.057    6.880    0.000
##     CognitivePrsnc       0.574    0.067    8.519    0.000
##   Care ~~
##     TeachingPresnc       0.223    0.044    5.076    0.000
##     SocialPresence       0.223    0.053    4.236    0.000
##     CognitivePrsnc       0.308    0.051    6.069    0.000
##   TeachingPresence ~~
##     SocialPresence       0.219    0.043    5.037    0.000
##     CognitivePrsnc       0.300    0.038    7.846    0.000
##   SocialPresence ~~
##     CognitivePrsnc       0.592    0.105    5.617    0.000
##
## Intercepts:
##                    Estimate  Std.Err  z-value  P(>|z|)
##    .M_2               5.168    0.069   74.643    0.000
##    .M_8               5.122    0.110   46.765    0.000
##    .M_12              4.845    0.085   56.740    0.000
##    .M_17              4.904    0.068   72.412    0.000
##    .M_26              4.759    0.078   60.844    0.000
##    .U_3               4.825    0.073   66.195    0.000
##    .U_5               4.917    0.075   65.811    0.000
##    .U_19              4.254    0.138   30.753    0.000
##    .U_21              4.594    0.100   46.165    0.000
##    .U_23              4.528    0.103   43.877    0.000
##    .S_7               5.036    0.067   75.569    0.000
##    .S_10              5.086    0.078   64.900    0.000
##    .S_14              5.135    0.066   78.372    0.000
##    .S_18              5.053    0.072   69.781    0.000
##    .I_1               4.710    0.077   60.999    0.000
##    .I_6               4.498    0.081   55.392    0.000
##    .I_9               4.594    0.091   50.325    0.000
##    .I_11              4.475    0.098   45.548    0.000
##    .I_13              4.459    0.112   39.933    0.000
##    .I_15              4.149    0.129   32.137    0.000
##    .C_4               5.419    0.051  106.028    0.000
##    .C_16              5.409    0.049  111.199    0.000
##    .C_20              5.191    0.062   83.538    0.000
##    .C_22              5.508    0.038  143.331    0.000
```

```
##    .C_24             5.512   0.036  152.718   0.000
##    .C_25             5.083   0.061   83.532   0.000
##    .TP_27            5.271   0.047  112.561   0.000
##    .TP_28            5.287   0.047  112.400   0.000
##    .TP_29            5.261   0.050  104.352   0.000
##    .TP_30            5.419   0.044  123.953   0.000
##    .TP_31            4.752   0.064   74.763   0.000
##    .TP_32            4.828   0.060   80.579   0.000
##    .TP_33            4.739   0.076   62.509   0.000
##    .TP_34            4.845   0.066   73.612   0.000
##    .TP_35            4.660   0.068   68.983   0.000
##    .TP_36            4.752   0.081   58.635   0.000
##    .TP_37            4.719   0.080   58.969   0.000
##    .TP_38            4.624   0.086   53.550   0.000
##    .TP_39            5.158   0.064   81.176   0.000
##    .SP_40            3.904   0.096   40.820   0.000
##    .SP_41            3.561   0.125   28.467   0.000
##    .SP_42            3.997   0.089   44.840   0.000
##    .SP_43            4.667   0.065   72.115   0.000
##    .SP_44            4.637   0.067   69.398   0.000
##    .SP_45            4.488   0.078   57.188   0.000
##    .SP_46            4.426   0.070   63.467   0.000
##    .SP_47            4.300   0.083   51.995   0.000
##    .SP_48            4.116   0.091   45.328   0.000
##    .CP_49            4.228   0.081   52.280   0.000
##    .CP_50            4.297   0.068   63.247   0.000
##    .CP_51            4.389   0.095   46.032   0.000
##    .CP_52            4.663   0.071   66.065   0.000
##    .CP_53            4.799   0.057   84.275   0.000
##    .CP_54            4.271   0.092   46.527   0.000
##    .CP_55            4.743   0.059   80.772   0.000
##    .CP_56            4.835   0.077   62.993   0.000
##    .CP_57            4.726   0.067   70.069   0.000
##    .CP_58            4.601   0.073   63.031   0.000
##    .CP_59            4.660   0.074   62.598   0.000
##    .CP_60            4.479   0.084   53.632   0.000
##     eMpowerment      0.000
##     Usefulness       0.000
##     Success          0.000
##     Interest         0.000
##     Care             0.000
##     TeachingPresnc   0.000
##     SocialPresence   0.000
```

```
##     CognitivePrsnc    0.000
##
## Variances:
##                      Estimate  Std.Err  z-value  P(>|z|)
##    .M_2                 0.434    0.066    6.526    0.000
##    .M_8                 0.487    0.074    6.567    0.000
##    .M_12                0.364    0.059    6.132    0.000
##    .M_17                0.447    0.068    6.612    0.000
##    .M_26                0.413    0.045    9.148    0.000
##    .U_3                 0.600    0.058   10.334    0.000
##    .U_5                 0.503    0.064    7.927    0.000
##    .U_19                0.365    0.070    5.242    0.000
##    .U_21                0.333    0.089    3.750    0.000
##    .U_23                0.304    0.054    5.590    0.000
##    .S_7                 0.212    0.033    6.451    0.000
##    .S_10                0.198    0.033    6.035    0.000
##    .S_14                0.383    0.058    6.584    0.000
##    .S_18                0.269    0.049    5.513    0.000
##    .I_1                 0.416    0.052    8.023    0.000
##    .I_6                 0.421    0.061    6.925    0.000
##    .I_9                 0.516    0.065    7.979    0.000
##    .I_11                0.305    0.038    7.978    0.000
##    .I_13                0.771    0.095    8.101    0.000
##    .I_15                0.828    0.118    7.048    0.000
##    .C_4                 0.226    0.024    9.502    0.000
##    .C_16                0.258    0.049    5.255    0.000
##    .C_20                0.339    0.067    5.039    0.000
##    .C_22                0.148    0.021    7.206    0.000
##    .C_24                0.127    0.020    6.245    0.000
##    .C_25                0.297    0.041    7.185    0.000
##    .TP_27               0.444    0.071    6.273    0.000
##    .TP_28               0.383    0.052    7.314    0.000
##    .TP_29               0.430    0.056    7.670    0.000
##    .TP_30               0.409    0.041    9.977    0.000
##    .TP_31               0.341    0.041    8.418    0.000
##    .TP_32               0.258    0.047    5.527    0.000
##    .TP_33               0.273    0.036    7.598    0.000
##    .TP_34               0.240    0.038    6.256    0.000
##    .TP_35               0.400    0.053    7.593    0.000
##    .TP_36               0.527    0.064    8.278    0.000
##    .TP_37               0.423    0.059    7.153    0.000
##    .TP_38               0.700    0.099    7.063    0.000
##    .TP_39               0.574    0.078    7.324    0.000
```

```
##    .SP_40             1.513    0.185    8.181    0.000
##    .SP_41             1.269    0.151    8.396    0.000
##    .SP_42             1.289    0.167    7.712    0.000
##    .SP_43             0.695    0.076    9.141    0.000
##    .SP_44             0.489    0.105    4.674    0.000
##    .SP_45             0.452    0.094    4.819    0.000
##    .SP_46             0.545    0.068    8.047    0.000
##    .SP_47             0.546    0.084    6.529    0.000
##    .SP_48             0.711    0.134    5.298    0.000
##    .CP_49             0.735    0.065   11.290    0.000
##    .CP_50             0.585    0.059    9.929    0.000
##    .CP_51             0.537    0.076    7.110    0.000
##    .CP_52             0.629    0.082    7.690    0.000
##    .CP_53             0.503    0.057    8.816    0.000
##    .CP_54             1.098    0.137    8.035    0.000
##    .CP_55             0.398    0.049    8.162    0.000
##    .CP_56             0.409    0.050    8.239    0.000
##    .CP_57             0.469    0.055    8.549    0.000
##    .CP_58             0.523    0.067    7.834    0.000
##    .CP_59             0.515    0.068    7.573    0.000
##    .CP_60             0.688    0.084    8.181    0.000
##     eMpowerment       0.670    0.176    3.802    0.000
##     Usefulness        0.548    0.098    5.587    0.000
##     Success           0.714    0.107    6.691    0.000
##     Interest          0.621    0.097    6.435    0.000
##     Care              0.374    0.073    5.105    0.000
##     TeachingPresnc    0.215    0.049    4.413    0.000
##     SocialPresence    0.798    0.172    4.637    0.000
##     CognitivePrsnc    0.853    0.119    7.142    0.000
```

Interpretation of Confirmatory Factor Analysis

The following lavaan WARNING was issued: *The variance-covariance matrix of the estimated parameters (vcov) does not appear to be positive definite! The smallest eigenvalue (= -2.143841e-14) is smaller than zero. This may be a symptom that the model is not identified.restarting interrupted promise evaluation.* Since this is barely below zero (to the 14th decimial place), it is most likely machine-precision issue and we can most likely ignore the issue (Kolenikov, 2018).

There are many different indices to measure confirmatory factor analyses. The four highlighted analyses in this study are the model chi-square, RMSEA, CFI, and SRMR. The model chi-square had a value of $p < .001$. However, you want to see the p-value be greater than .05 in order for this to be a good fit. The RMSEA value should be less than .08 to indicate good fit and the analysis performed above found the model to have a value of .079 which is borderline on being a good fit. The CFI should be greater than or equal to .90 and the model in this study was at .799 which did not make the cut-off. A SRMR good-fit should be less than .08 and this model had a value of .067 which did make the cut-off. Overall, of the 4 common factor analyses chosen, 2 passed the test and 2 did not. The chi-square measurement is an absolute fit index and with the complexity of the model along with sample size this limits the ability to find an absolute goodness of fit model. The small discrepancies of the other three reported indices (two meeting the threshold and one not) is most likely due to the model complexity.

For an exploratory study of this nature, measuring eight different factors and 60 items, there are issues with good fit of the model due to model complexity. Using the data to find factors that have association to course persistence and retention and modifying the model to improve the fitness would result in more valid data in future studies.

eMpowerment Cronbach Alpha

```
data_raw %>%
  dplyr::select(M_2, M_8, M_12, M_17, M_26) %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean   sd median_r
##       0.91      0.91    0.89      0.67  10 0.0079  4.9 0.99     0.67
##
##  lower alpha upper     95% confidence boundaries
## 0.89 0.91 0.93
##
##  Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r S/N alpha se   var.r med.r
## M_2       0.89      0.89    0.86      0.67 8.2   0.0098 0.00038  0.67
## M_8       0.89      0.89    0.86      0.66 7.9   0.0101 0.00176  0.67
## M_12      0.89      0.89    0.86      0.66 7.8   0.0102 0.00153  0.67
## M_17      0.89      0.89    0.87      0.68 8.3   0.0097 0.00118  0.68
## M_26      0.89      0.89    0.86      0.67 8.1   0.0099 0.00127  0.67
##
##  Item statistics
##        n raw.r std.r r.cor r.drop mean  sd
## M_2  329  0.85  0.85  0.81   0.76  5.1 1.1
## M_8  330  0.86  0.86  0.82   0.78  5.1 1.2
## M_12 329  0.86  0.87  0.83   0.79  4.8 1.1
## M_17 329  0.85  0.85  0.79   0.76  4.9 1.1
## M_26 329  0.86  0.86  0.81   0.77  4.8 1.2
##
## Non missing response frequency for each item
##         1    2    3    4    5    6 miss
## M_2  0.02 0.02 0.02 0.10 0.38 0.44    0
## M_8  0.02 0.03 0.05 0.12 0.29 0.49    0
## M_12 0.01 0.04 0.06 0.17 0.42 0.29    0
## M_17 0.02 0.02 0.06 0.18 0.37 0.34    0
## M_26 0.02 0.03 0.08 0.21 0.34 0.31    0
```

Usefulness Cronbach Alpha

```
data_raw %>%
  dplyr::select(U_3, U_5, U_19, U_21, U_23) %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean sd median_r
##       0.91      0.91    0.92      0.67  10 0.0081  4.6  1     0.62
##
##  lower alpha upper     95% confidence boundaries
## 0.89 0.91 0.92
##
##  Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## U_3       0.91      0.91    0.89      0.71 9.9   0.0081 0.012  0.71
## U_5       0.89      0.89    0.88      0.67 8.3   0.0094 0.023  0.67
## U_19      0.88      0.89    0.89      0.66 7.7   0.0109 0.014  0.62
## U_21      0.88      0.88    0.90      0.65 7.5   0.0113 0.020  0.60
## U_23      0.88      0.88    0.89      0.65 7.5   0.0113 0.014  0.62
##
##  Item statistics
##        n raw.r std.r r.cor r.drop mean  sd
## U_3  329  0.78  0.80  0.75   0.67  4.8 1.1
## U_5  328  0.84  0.85  0.82   0.75  4.9 1.1
## U_19 330  0.89  0.87  0.85   0.80  4.2 1.4
## U_21 330  0.89  0.88  0.85   0.82  4.6 1.2
## U_23 330  0.89  0.88  0.86   0.82  4.5 1.3
##
## Non missing response frequency for each item
##         1    2    3    4    5    6 miss
## U_3  0.02 0.04 0.03 0.23 0.38 0.30 0.00
## U_5  0.02 0.02 0.03 0.20 0.40 0.32 0.01
## U_19 0.05 0.08 0.13 0.28 0.25 0.22 0.00
## U_21 0.03 0.03 0.09 0.22 0.41 0.22 0.00
## U_23 0.03 0.04 0.10 0.27 0.30 0.26 0.00
```

Success Cronbach Alpha

```
data_raw %>%
  dplyr::select(S_7, S_10, S_14, S_18) %>%
  psych::alpha()

##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean   sd median_r
##       0.91      0.91    0.89      0.73  11 0.0078    5 0.91     0.73
##
##  lower alpha upper     95% confidence boundaries
## 0.9 0.91 0.93
##
##  Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r S/N alpha se  var.r med.r
## S_7       0.87      0.87    0.82      0.69 6.7   0.0125 0.0014  0.67
## S_10      0.88      0.88    0.83      0.71 7.3   0.0115 0.0011  0.73
## S_14      0.91      0.91    0.87      0.76 9.6   0.0091 0.0029  0.73
## S_18      0.89      0.89    0.86      0.74 8.5   0.0102 0.0061  0.73
##
##  Item statistics
##        n raw.r std.r r.cor r.drop mean sd
## S_7  329  0.92  0.92  0.90   0.85  5.0  1
## S_10 330  0.90  0.91  0.87   0.83  5.0  1
## S_14 330  0.86  0.86  0.78   0.75  5.1  1
## S_18 329  0.88  0.88  0.81   0.78  5.0  1
##
## Non missing response frequency for each item
##         1    2    3    4    5    6 miss
## S_7  0.01 0.02 0.05 0.17 0.39 0.36    0
## S_10 0.01 0.02 0.04 0.13 0.43 0.36    0
## S_14 0.02 0.02 0.04 0.12 0.42 0.39    0
## S_18 0.01 0.02 0.04 0.16 0.41 0.36    0
```

Interest Cronbach Alpha

```
data_raw %>%
  dplyr::select(I_1, I_6, I_9, I_11, I_13, I_15) %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean sd median_r
##       0.91      0.91     0.9      0.62 9.9 0.0082  4.5  1     0.62
##
##  lower alpha upper     95% confidence boundaries
## 0.89 0.91 0.92
##
##  Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r S/N alpha se  var.r med.r
## I_1       0.89      0.89    0.89      0.62 8.2   0.0100 0.0092  0.62
## I_6       0.88      0.89    0.88      0.61 7.9   0.0101 0.0052  0.62
## I_9       0.89      0.89    0.88      0.63 8.4   0.0096 0.0046  0.62
## I_11      0.88      0.88    0.87      0.60 7.4   0.0108 0.0068  0.59
## I_13      0.89      0.90    0.89      0.64 8.8   0.0094 0.0079  0.65
## I_15      0.90      0.90    0.89      0.65 9.1   0.0089 0.0060  0.65
##
##  Item statistics
##        n raw.r std.r r.cor r.drop mean  sd
## I_1  329  0.82  0.83  0.79   0.75  4.7 1.1
## I_6  330  0.84  0.85  0.82   0.77  4.5 1.2
## I_9  330  0.82  0.82  0.79   0.73  4.6 1.2
## I_11 330  0.88  0.88  0.86   0.82  4.5 1.2
## I_13 330  0.81  0.80  0.75   0.71  4.4 1.3
## I_15 329  0.81  0.78  0.73   0.69  4.1 1.4
##
## Non missing response frequency for each item
##         1    2    3    4    5    6 miss
## I_1  0.01 0.04 0.05 0.25 0.43 0.21    0
## I_6  0.03 0.05 0.08 0.29 0.37 0.18    0
## I_9  0.02 0.06 0.08 0.23 0.37 0.23    0
## I_11 0.02 0.06 0.07 0.31 0.36 0.17    0
## I_13 0.04 0.07 0.09 0.25 0.33 0.22    0
## I_15 0.05 0.09 0.12 0.30 0.26 0.17    0
```

Care Cronbach Alpha

```
data_raw %>%
  dplyr::select(C_4, C_16, C_20, C_22, C_24, C_25) %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean   sd median_r
##        0.9      0.91     0.9      0.62 9.8 0.0083  5.3 0.67     0.61
##
##  lower alpha upper     95% confidence boundaries
## 0.89 0.9 0.92
##
##  Reliability if an item is dropped:
##      raw_alpha std.alpha G6(smc) average_r S/N alpha se  var.r med.r
## C_4       0.88      0.89    0.87      0.62 8.3   0.0098 0.0024  0.61
## C_16      0.88      0.89    0.87      0.62 8.2   0.0101 0.0034  0.62
## C_20      0.89      0.90    0.88      0.63 8.5   0.0097 0.0042  0.62
## C_22      0.89      0.89    0.88      0.62 8.1   0.0099 0.0039  0.62
## C_24      0.88      0.89    0.87      0.61 7.7   0.0102 0.0031  0.60
## C_25      0.89      0.89    0.88      0.63 8.4   0.0097 0.0030  0.62
##
##  Item statistics
##        n raw.r std.r r.cor r.drop mean   sd
## C_4  328  0.82  0.82  0.79   0.73  5.4 0.85
## C_16 330  0.83  0.83  0.79   0.75  5.4 0.87
## C_20 330  0.82  0.81  0.75   0.72  5.2 0.93
## C_22 329  0.81  0.83  0.79   0.75  5.5 0.65
## C_24 330  0.84  0.85  0.83   0.78  5.5 0.67
## C_25 329  0.83  0.82  0.77   0.73  5.1 0.92
##
## Non missing response frequency for each item
##         1    2    3    4    5    6 miss
## C_4  0.01 0.01 0.02 0.08 0.34 0.55 0.01
## C_16 0.01 0.01 0.02 0.06 0.35 0.55 0.00
## C_20 0.01 0.01 0.01 0.16 0.37 0.44 0.00
## C_22 0.00 0.00 0.01 0.04 0.40 0.56 0.00
## C_24 0.00 0.00 0.01 0.05 0.37 0.57 0.00
## C_25 0.01 0.01 0.04 0.18 0.40 0.37 0.00
```

Teaching Presence Cronbach Alpha

```
data_raw %>%
  dplyr::select(TP_27, TP_28, TP_29, TP_30, TP_31, TP_32, TP_33,
                TP_34, TP_35, TP_36, TP_37, TP_38, TP_39) %>%
  psych::alpha()

##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean  sd median_r
##       0.94      0.94    0.96      0.57  17 0.0044    5 0.8     0.54
##
##  lower alpha upper     95% confidence boundaries
## 0.94 0.94 0.95
##
##  Reliability if an item is dropped:
##       raw_alpha std.alpha G6(smc) average_r S/N alpha se var.r med.r
## TP_27      0.94      0.94    0.96      0.58  17   0.0045 0.019  0.55
## TP_28      0.94      0.94    0.95      0.57  16   0.0046 0.020  0.53
## TP_29      0.94      0.94    0.96      0.57  16   0.0045 0.020  0.55
## TP_30      0.94      0.94    0.96      0.58  17   0.0044 0.018  0.55
## TP_31      0.94      0.94    0.96      0.56  15   0.0049 0.020  0.53
## TP_32      0.94      0.94    0.96      0.56  15   0.0050 0.019  0.53
## TP_33      0.94      0.94    0.95      0.55  15   0.0050 0.018  0.53
## TP_34      0.94      0.94    0.95      0.55  15   0.0050 0.018  0.53
## TP_35      0.94      0.94    0.96      0.56  15   0.0050 0.019  0.53
## TP_36      0.94      0.94    0.96      0.57  16   0.0047 0.018  0.54
## TP_37      0.94      0.94    0.95      0.56  15   0.0049 0.019  0.54
## TP_38      0.94      0.94    0.96      0.57  16   0.0046 0.021  0.53
## TP_39      0.94      0.94    0.96      0.58  17   0.0045 0.021  0.56
##
##  Item statistics
##         n raw.r std.r r.cor r.drop mean   sd
## TP_27 330  0.67  0.69  0.67   0.62  5.3 0.84
## TP_28 330  0.74  0.77  0.76   0.70  5.3 0.88
## TP_29 330  0.72  0.75  0.73   0.67  5.2 0.90
## TP_30 330  0.63  0.65  0.62   0.57  5.4 0.82
## TP_31 329  0.84  0.83  0.81   0.80  4.8 1.07
## TP_32 329  0.85  0.84  0.83   0.82  4.8 1.05
## TP_33 329  0.87  0.86  0.85   0.84  4.7 1.12
## TP_34 329  0.87  0.86  0.86   0.85  4.9 1.06
```

```
## TP_35 328  0.84  0.83  0.82   0.81  4.7 1.16
## TP_36 330  0.77  0.75  0.73   0.72  4.8 1.11
## TP_37 330  0.84  0.82  0.81   0.80  4.7 1.15
## TP_38 330  0.75  0.73  0.71   0.69  4.6 1.15
## TP_39 330  0.68  0.68  0.64   0.62  5.1 0.98
##
## Non missing response frequency for each item
##          1    2    3    4    5    6 miss
## TP_27 0.01 0.00 0.02 0.12 0.40 0.45 0.00
## TP_28 0.01 0.02 0.02 0.08 0.42 0.46 0.00
## TP_29 0.01 0.01 0.03 0.10 0.39 0.46 0.00
## TP_30 0.01 0.01 0.01 0.08 0.34 0.55 0.00
## TP_31 0.02 0.03 0.05 0.25 0.40 0.26 0.00
## TP_32 0.01 0.02 0.07 0.18 0.44 0.27 0.00
## TP_33 0.02 0.03 0.07 0.23 0.38 0.27 0.00
## TP_34 0.02 0.03 0.05 0.19 0.44 0.28 0.00
## TP_35 0.02 0.03 0.09 0.22 0.38 0.26 0.01
## TP_36 0.02 0.02 0.09 0.21 0.38 0.29 0.00
## TP_37 0.02 0.04 0.08 0.22 0.36 0.28 0.00
## TP_38 0.01 0.05 0.09 0.27 0.33 0.26 0.00
## TP_39 0.01 0.01 0.05 0.15 0.33 0.45 0.00
```

Social Presence Cronbach Alpha

```
data_raw %>%
  dplyr::select(SP_40, SP_41, SP_42, SP_43, SP_44,
                SP_45, SP_46, SP_47, SP_48) %>%
  psych::alpha()

##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean sd median_r
##       0.91      0.92    0.93      0.55  11 0.0073  4.2  1     0.56
##
##  lower alpha upper     95% confidence boundaries
## 0.9 0.91 0.93
##
##  Reliability if an item is dropped:
##       raw_alpha std.alpha G6(smc) average_r  S/N alpha se var.r med.r
## SP_40      0.91      0.92    0.93      0.58 10.9   0.0074 0.013  0.58
## SP_41      0.91      0.91    0.92      0.56 10.3   0.0079 0.015  0.57
## SP_42      0.91      0.91    0.92      0.56 10.3   0.0078 0.016  0.58
## SP_43      0.91      0.91    0.92      0.56 10.0   0.0080 0.015  0.56
## SP_44      0.90      0.90    0.91      0.54  9.5   0.0083 0.011  0.56
## SP_45      0.90      0.90    0.91      0.53  9.2   0.0085 0.011  0.56
## SP_46      0.90      0.90    0.92      0.54  9.4   0.0084 0.014  0.56
## SP_47      0.90      0.90    0.92      0.54  9.3   0.0085 0.017  0.55
## SP_48      0.90      0.90    0.92      0.54  9.3   0.0086 0.017  0.54
##
##  Item statistics
##         n raw.r std.r r.cor r.drop mean  sd
## SP_40 330  0.69  0.67  0.62   0.59  3.9 1.5
## SP_41 330  0.74  0.73  0.69   0.66  3.6 1.5
## SP_42 330  0.73  0.72  0.68   0.65  4.0 1.5
## SP_43 330  0.74  0.75  0.71   0.67  4.6 1.2
## SP_44 330  0.79  0.80  0.80   0.73  4.6 1.2
## SP_45 328  0.83  0.84  0.84   0.78  4.5 1.3
## SP_46 330  0.80  0.81  0.79   0.75  4.4 1.3
## SP_47 330  0.82  0.82  0.80   0.77  4.3 1.3
## SP_48 330  0.82  0.82  0.80   0.77  4.1 1.4
##
## Non missing response frequency for each item
##          1    2    3    4    5    6 miss
```

```
## SP_40 0.08 0.13 0.17 0.23 0.22 0.17 0.00
## SP_41 0.09 0.17 0.18 0.28 0.17 0.11 0.00
## SP_42 0.05 0.14 0.14 0.26 0.24 0.17 0.00
## SP_43 0.02 0.05 0.08 0.22 0.35 0.27 0.00
## SP_44 0.02 0.07 0.06 0.18 0.42 0.23 0.00
## SP_45 0.03 0.09 0.06 0.25 0.36 0.21 0.01
## SP_46 0.04 0.06 0.09 0.28 0.34 0.19 0.00
## SP_47 0.04 0.07 0.08 0.32 0.34 0.15 0.00
## SP_48 0.05 0.09 0.13 0.28 0.28 0.15 0.00
```

Cognitive Presence Cronbach Alpha

```
data_raw %>%
  dplyr::select(CP_49, CP_50, CP_51, CP_52, CP_53, CP_54,
                CP_55, CP_56, CP_57, CP_58, CP_59, CP_60) %>%
  psych::alpha()
```

```
##
## Reliability analysis
## Call: psych::alpha(x = .)
##
##   raw_alpha std.alpha G6(smc) average_r S/N    ase mean  sd median_r
##       0.94      0.94    0.95      0.57  16 0.0051  4.5 0.9     0.56
##
##  lower alpha upper     95% confidence boundaries
## 0.93 0.94 0.95
##
##  Reliability if an item is dropped:
##       raw_alpha std.alpha G6(smc) average_r S/N alpha se  var.r med.r
## CP_49      0.93      0.94    0.94      0.57  15   0.0055 0.0067  0.57
## CP_50      0.93      0.93    0.94      0.56  14   0.0056 0.0066  0.56
## CP_51      0.93      0.93    0.94      0.56  14   0.0058 0.0065  0.55
## CP_52      0.93      0.93    0.94      0.56  14   0.0056 0.0061  0.56
## CP_53      0.93      0.93    0.94      0.56  14   0.0055 0.0059  0.56
## CP_54      0.94      0.94    0.95      0.58  15   0.0051 0.0045  0.57
## CP_55      0.93      0.93    0.94      0.56  14   0.0056 0.0068  0.55
## CP_56      0.93      0.93    0.94      0.56  14   0.0055 0.0070  0.55
## CP_57      0.93      0.94    0.94      0.57  15   0.0055 0.0070  0.56
## CP_58      0.93      0.93    0.94      0.56  14   0.0055 0.0058  0.56
## CP_59      0.93      0.93    0.94      0.57  14   0.0055 0.0054  0.56
## CP_60      0.93      0.94    0.94      0.57  14   0.0055 0.0065  0.56
##
##  Item statistics
##         n raw.r std.r r.cor r.drop mean   sd
## CP_49 328  0.76  0.75  0.73   0.71  4.2 1.26
## CP_50 329  0.79  0.79  0.77   0.75  4.3 1.20
## CP_51 330  0.83  0.83  0.81   0.79  4.4 1.31
## CP_52 329  0.80  0.80  0.78   0.75  4.6 1.23
## CP_53 329  0.78  0.78  0.77   0.73  4.8 1.08
## CP_54 330  0.69  0.68  0.64   0.61  4.2 1.39
## CP_55 329  0.81  0.81  0.79   0.77  4.7 1.02
## CP_56 330  0.78  0.79  0.77   0.74  4.8 0.99
## CP_57 328  0.75  0.76  0.73   0.70  4.7 1.02
```

```
## CP_58 328  0.78  0.78  0.77   0.73  4.6 1.11
## CP_59 328  0.77  0.77  0.76   0.72  4.7 1.09
## CP_60 330  0.77  0.77  0.74   0.72  4.5 1.27
##
## Non missing response frequency for each item
##          1    2    3    4    5    6 miss
## CP_49 0.03 0.06 0.15 0.31 0.28 0.16 0.01
## CP_50 0.02 0.07 0.11 0.36 0.28 0.16 0.00
## CP_51 0.04 0.07 0.10 0.28 0.31 0.21 0.00
## CP_52 0.02 0.06 0.08 0.22 0.34 0.28 0.00
## CP_53 0.01 0.02 0.07 0.23 0.39 0.28 0.00
## CP_54 0.05 0.09 0.10 0.28 0.30 0.18 0.00
## CP_55 0.01 0.03 0.06 0.29 0.39 0.23 0.00
## CP_56 0.01 0.03 0.04 0.25 0.41 0.27 0.00
## CP_57 0.01 0.03 0.06 0.26 0.41 0.23 0.01
## CP_58 0.02 0.04 0.09 0.26 0.40 0.21 0.01
## CP_59 0.01 0.04 0.06 0.26 0.41 0.22 0.01
## CP_60 0.02 0.07 0.09 0.27 0.30 0.25 0.00
```

Interpretation of Cronbach Alphas

The calculated Cronbach alphas for each of the three learning environment factors and the five motivational factors were higher than .90, which indicated that there was internal consistency and reliability between the items used to measure the factors. However, high intercorrelations, or Cronbach alpha values might indicate that the items are "overly redundant and the construct measured too specific" (Briggs & Cheek, 1986, p. 114). Therefore, the concern for this study was that with 60 measured items there may have been redundant items in the instrument. This is particularly true with the learning environment factors of Teaching Presence (.94) and Cognitive Presence (.94).

Descriptive Statistics

The researcher ran a descriptive statistics table for each of the five motivational factors and the three learning environment factors (see Tables J.1 and J.2). Then, a histogram was generated for each of the eight variables to check for normal data distribution (see Figures J.1, J.2, J.3, J.4, J.5, J.6, J.7, J.8). Lastly, Skewness and Kurtosis was checked for each of the eight factors (see Table J.3). Interpretations of each of descriptive analyses was added after the analysis was performed in R.

Descriptive Table – Total Mean (SD): Grouping with notCompleted with p-value

```
data_clean %>%
  dplyr::group_by(notCompleted) %>%
  furniture::table1(M_Subscore, U_Subscore, S_Subscore, I_Subscore,
                    C_Subscore, TP_Subscore, SP_Subscore, CP_Subscore,
                    na.rm= FALSE,
                    total = TRUE,
                    test = TRUE,
                    digits = 3,
                    output = "latex2",
                    label = "tab:Descriptive",
                    caption = "Total Mean (SD): Grouping with
                    variable notCompleted with independent t-tests")
```

Table J.1

Total Mean (SD): Grouping with variable notCompleted with independent t-tests

		notCompleted		
	Total	0	1	P-Value
	n = 330	n = 226	n = 104	
M_Subscore				0.281
	4.935 (0.986)	4.975 (0.927)	4.849 (1.102)	
U_Subscore				0.029
	4.621 (1.042)	4.705 (0.983)	4.437 (1.145)	
S_Subscore				0.008
	5.039 (0.909)	5.129 (0.817)	4.843 (1.060)	
I_Subscore				0.039
	4.461 (1.011)	4.539 (0.962)	4.292 (1.096)	
C_Subscore				0.63
	5.338 (0.674)	5.350 (0.657)	5.311 (0.710)	
TP_Subscore				0.845
	4.951 (0.799)	4.945 (0.790)	4.964 (0.822)	
SP_Subscore				0.114
	4.223 (1.037)	4.162 (1.031)	4.356 (1.043)	
CP_Subscore				0.399
	4.549 (0.902)	4.577 (0.851)	4.487 (1.006)	

Descriptive Table – Total Mean (SD): Grouping with EnrolledSpring2019 with p-value

```
data_clean %>%
  dplyr::group_by(EnrolledSpring2019) %>%
  furniture::table1(M_Subscore, U_Subscore, S_Subscore, I_Subscore,
                    C_Subscore, TP_Subscore, SP_Subscore, CP_Subscore,
                    na.rm= FALSE,
                    total = TRUE,
                    test = TRUE,
                    digits = 3,
                    output = "latex2",
                    label = "tab:Descriptive2",
                    caption = "Total Mean (SD): Grouping with
                    EnrolledSpring2019 with p-value")
```

Table J.2

Total Mean (SD): Grouping with EnrolledSpring2019 with p-value

		EnrolledSpring2019		
	Total	N	Y	P-Value
	n = 330	n = 129	n = 201	
M_Subscore				0.136
	4.935 (0.986)	4.834 (1.131)	5.000 (0.877)	
U_Subscore				0.57
	4.621 (1.042)	4.580 (1.134)	4.647 (0.981)	
S_Subscore				0.494
	5.039 (0.909)	4.994 (1.054)	5.068 (0.804)	
I_Subscore				0.131
	4.461 (1.011)	4.356 (1.115)	4.528 (0.935)	
C_Subscore				0.957
	5.338 (0.674)	5.340 (0.703)	5.336 (0.656)	
TP_Subscore				0.87
	4.951 (0.799)	4.942 (0.849)	4.957 (0.767)	
SP_Subscore				0.423
	4.223 (1.037)	4.280 (1.049)	4.186 (1.030)	
CP_Subscore				0.93
	4.549 (0.902)	4.543 (0.950)	4.552 (0.872)	

Interpretation of Descriptive Tables

The mean and standard deviation for each of the eight factors indicates which were the highest perceived factors in the online developmental mathematics courses (see Table J.1). Motivational factors of Success and Care had the highest mean values of student perceptions (5.039 and 5.338 respectively). The lowest mean scores of student perceptions, in student online developmental mathematics classes, was Interest and Social Presence (4.461 and 4.223 respectively). An analysis also was performed measuring the different means between students that completed and students who did not complete the class for each of the eight factors. Almost all factors showed that students who completed the course on average had a higher mean value of perception except for Teaching Presence and Social Presence. Teaching Presence was almost equal in mean values. Social Presence indicated the highest amount of difference with a mean of 4.162 for students who completed the course compared to 4.356 for those who did not complete.

The seperated grouping and bivariate analysis was also performed for students who enrolled in a mathematics course for the Spring 2019 semester (see Table J.2). None of factors showed major differences between the means of the eight factors measured.

Histogram of eMpowerment

```
data_clean %>%
  ggplot(aes(x = M_Subscore)) +
  geom_histogram(aes(y = ..density..),
                 binwidth = 0.5,
                 alpha = 0.5,
                 position = "identity") +
  geom_density(linetype = "dotted") +
  geom_density(adjust = 2) +
  theme_bw() +
  labs(x = "eMpowerment Factor (scale 1-6)")
```

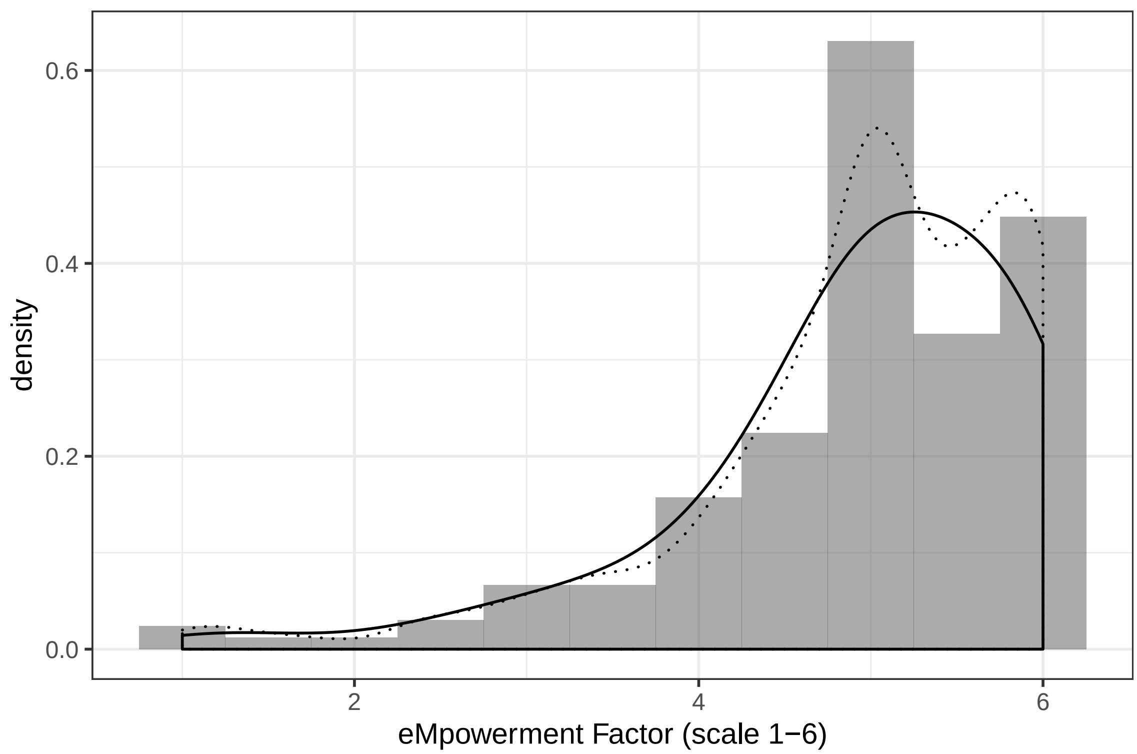

Figure J.1. Univariate Distribution of eMpowerment Scores

Histogram of Usefulness

```
data_clean %>%
  ggplot(aes(x = U_Subscore)) +
  geom_histogram(aes(y = ..density..),
                 binwidth = 0.5,
                 alpha = 0.5,
                 position = "identity") +
  geom_density(linetype = "dotted") +
  geom_density(adjust = 2) +
  theme_bw() +
  labs(x = "Usefulness Factor (scale 1-6)")
```

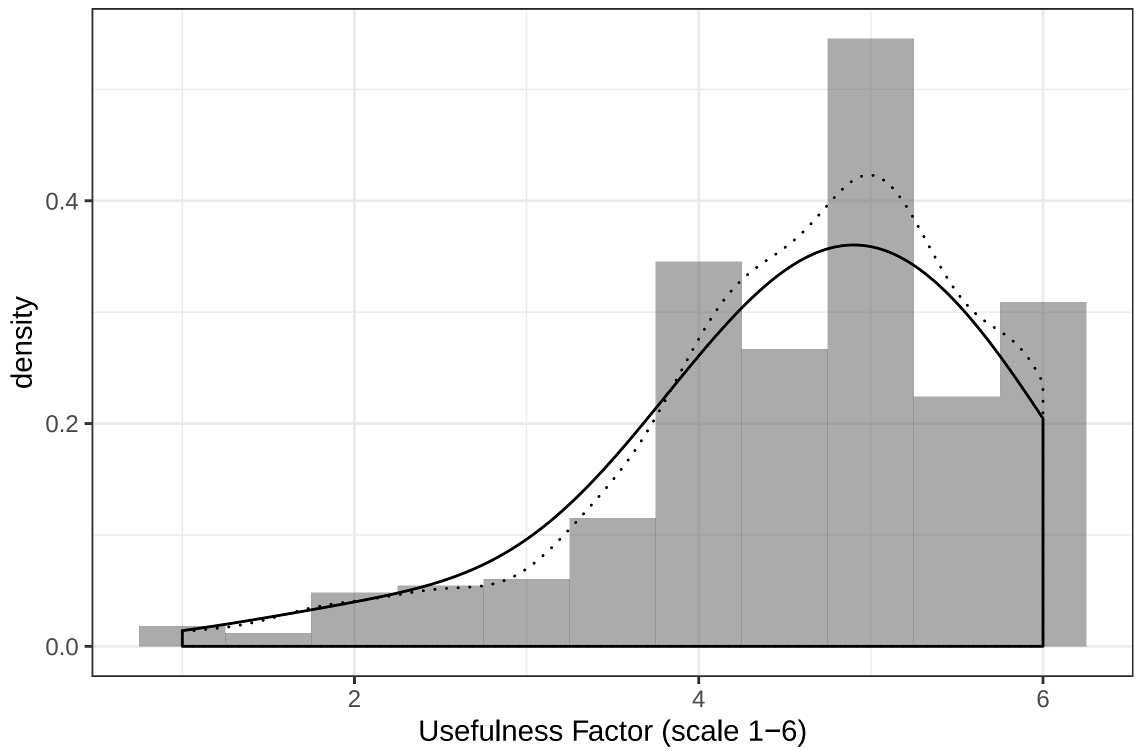

Figure J.2. Univariate Distribution of Usefulness Scores

Histogram of Success

```
data_clean %>%
  ggplot(aes(x = S_Subscore)) +
  geom_histogram(aes(y = ..density..),
                 binwidth = 0.5,
                 alpha = 0.5,
                 position = "identity") +
  geom_density(linetype = "dotted") +
  geom_density(adjust = 2) +
  theme_bw() +
  labs(x = "Success Factor scale (1-6)")
```

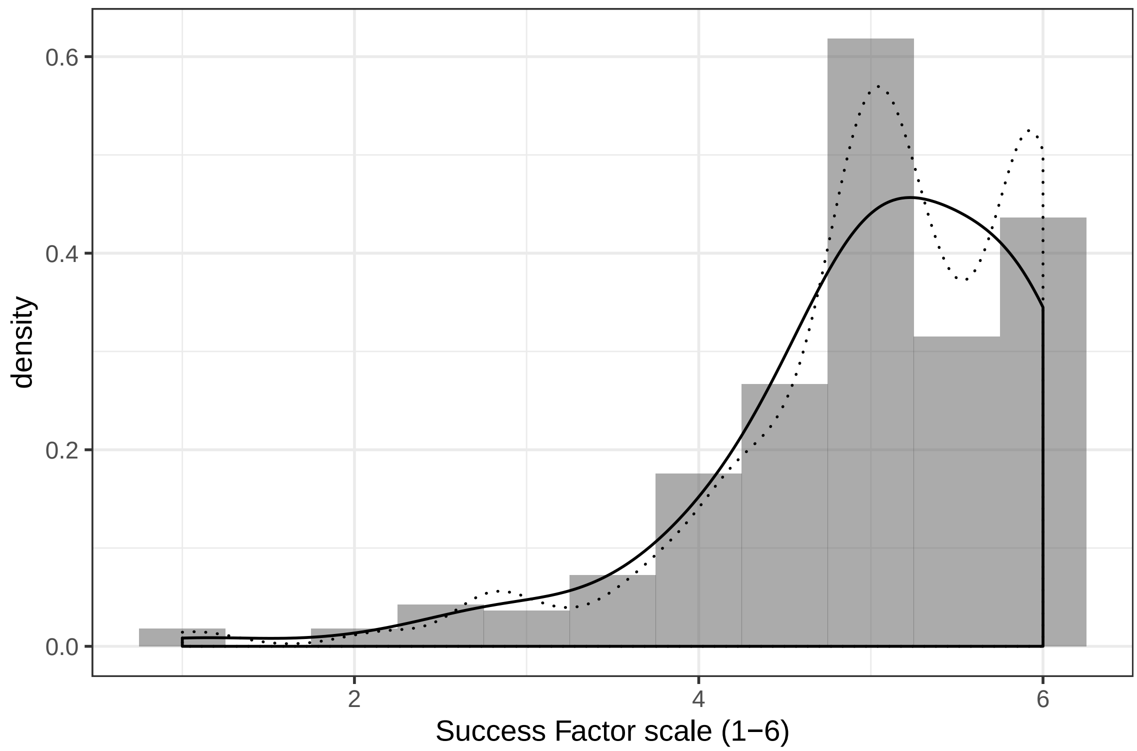

Figure J.3. Univariate Distribution of Success Scores

Histogram of Interest

```
data_clean %>%
  ggplot(aes(x = I_Subscore)) +
  geom_histogram(aes(y = ..density..),
                 binwidth = 0.5,
                 alpha = 0.5,
                 position = "identity") +
  geom_density(linetype = "dotted") +
  geom_density(adjust = 2) +
  theme_bw() +
  labs(x = "Interest Factor (scale 1-6)")
```

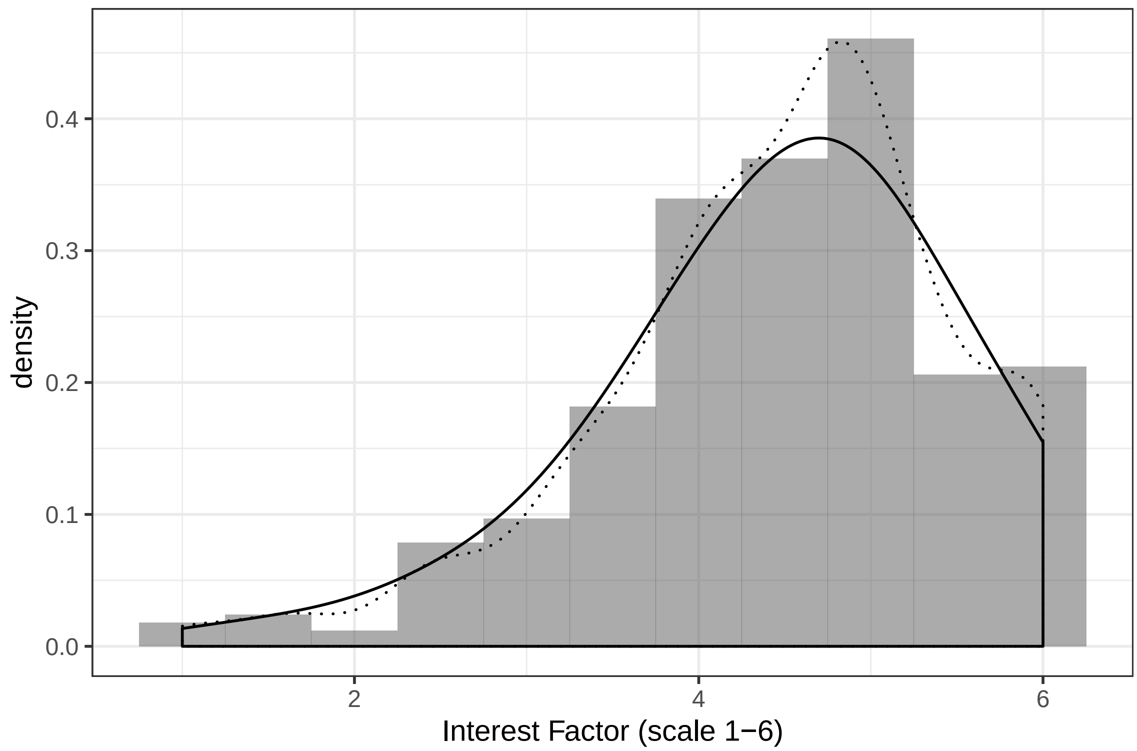

Figure J.4. Univariate Distribution of Interest Scores

Histogram of Care

```
data_clean %>%
  ggplot(aes(x = C_Subscore)) +
  geom_histogram(aes(y = ..density..),
                 binwidth = 0.5,
                 alpha = 0.5,
                 position = "identity") +
  geom_density(linetype = "dotted") +
  geom_density(adjust = 2) +
  theme_bw() +
  labs(x = "Care Factor (scale 1-6)")
```

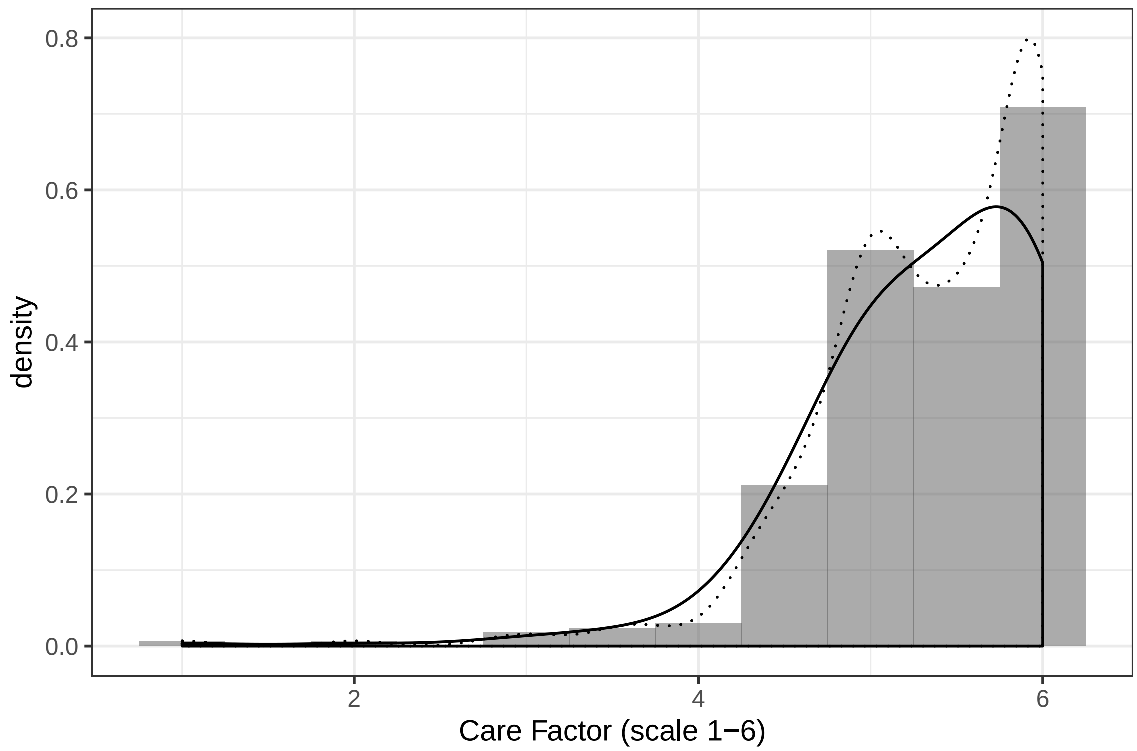

Figure J.5. Univariate Distribution of Care Scores

Histogram of Teaching Presence

```
data_clean %>%
  ggplot(aes(x = TP_Subscore)) +
  geom_histogram(aes(y = ..density..),
                 binwidth = 0.5,
                 alpha = 0.5,
                 position = "identity") +
  geom_density(linetype = "dotted") +
  geom_density(adjust = 2) +
  theme_bw() +
  labs(x = "Teaching Presence Factor (scale 1-6)")
```

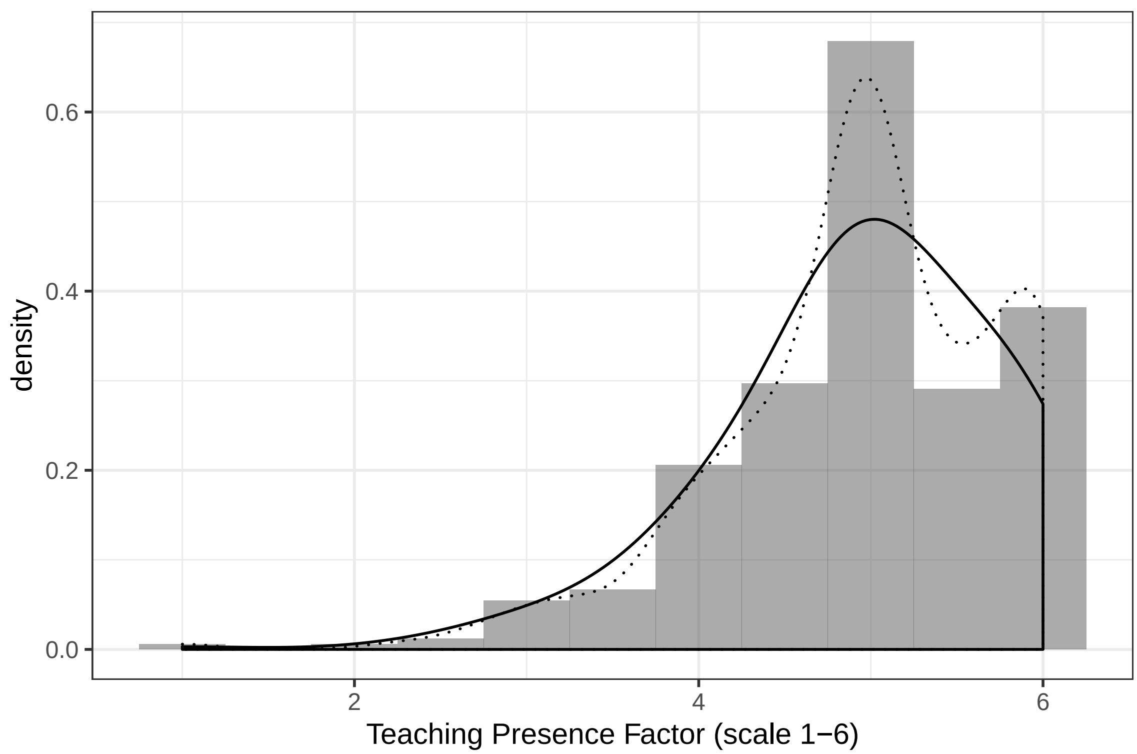

Figure J.6. Univariate Distribution of Teaching Presence Scores

Histogram of Social Presence

```
data_clean %>%
  ggplot(aes(x = SP_Subscore)) +
  geom_histogram(aes(y = ..density..),
                 binwidth = 0.5,
                 alpha = 0.5,
                 position = "identity") +
  geom_density(linetype = "dotted") +
  geom_density(adjust = 2) +
  theme_bw() +
  labs(x = "Social Presence Factor (scale 1-6)")
```

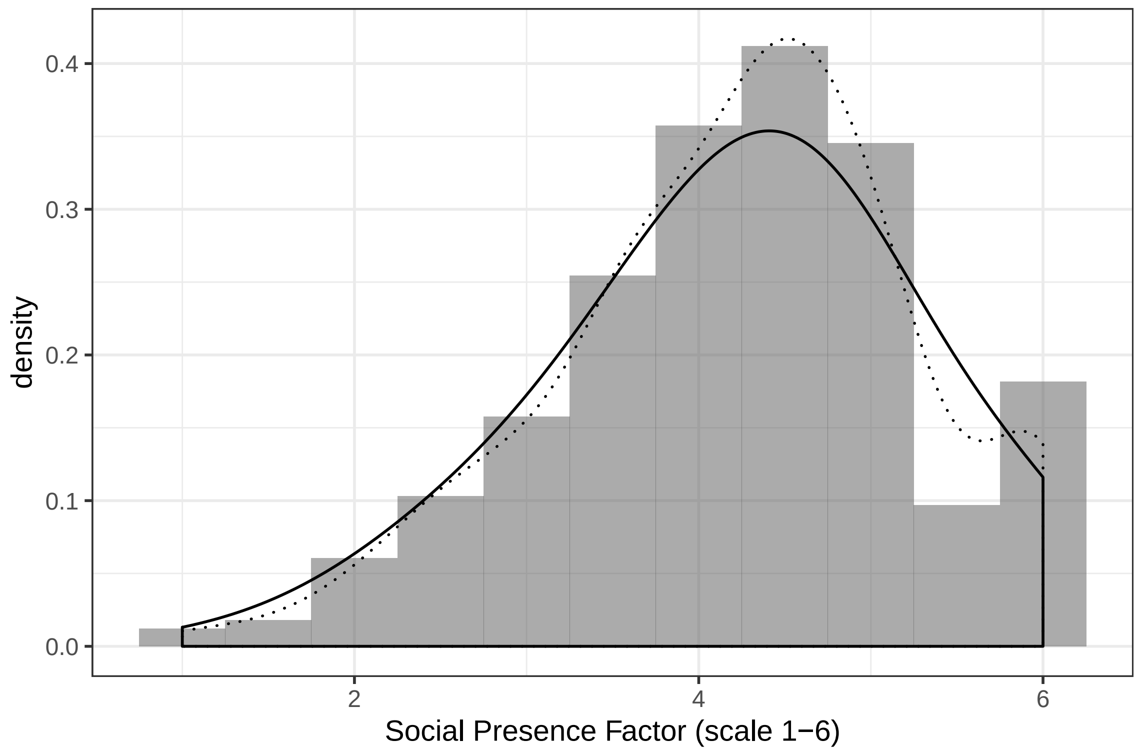

Figure J.7. Univariate Distribution of Social Presence Scores

Histogram of Cognitive Presence

```
data_clean %>%
  ggplot(aes(x = CP_Subscore)) +
  geom_histogram(aes(y = ..density..),
                 binwidth = 0.5,
                 alpha = 0.5,
                 position = "identity") +
  geom_density(linetype = "dotted") +
  geom_density(adjust = 2) +
  theme_bw() +
  labs(x = "Cognitive Presence Factor (scale 1-6)")
```

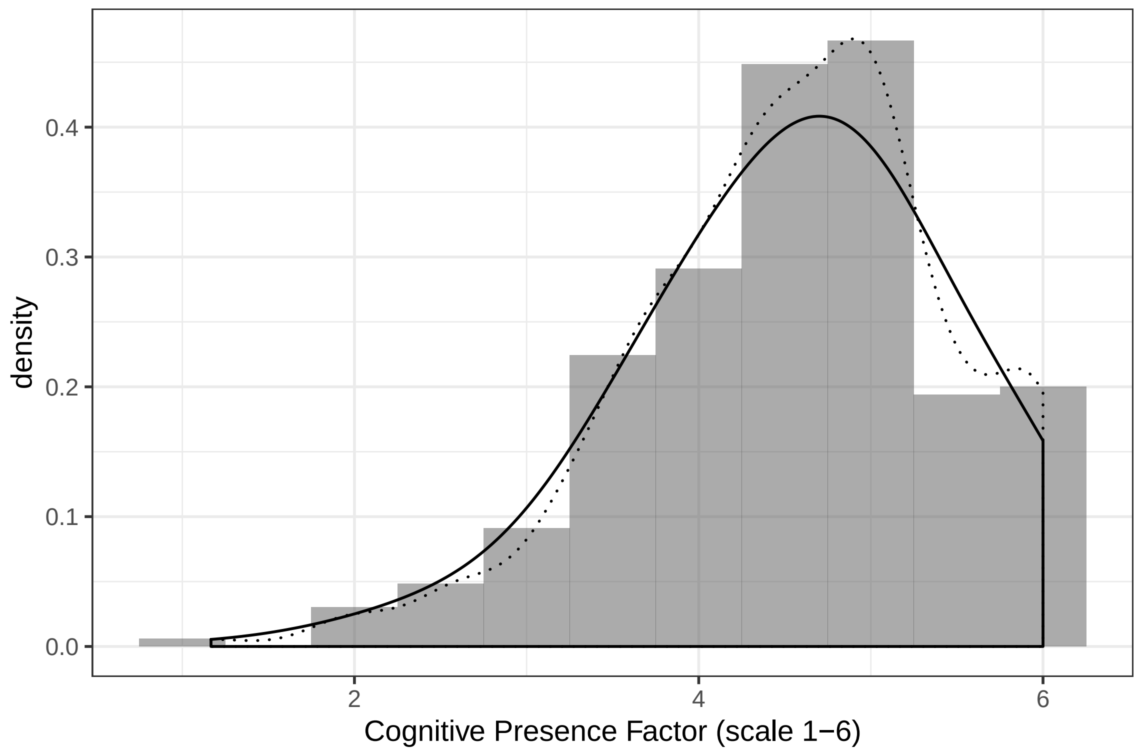

Figure J.8. Univariate Distribution of Cognitive Presence Scores

Interpretation of Histograms

The histograms demonstrated that not all the factors followed a traditional normal distribution. The plots indicated that most of the distributions were left-skewed with the tail on the left side of the distribution. In order to get a clearer picture, the researcher next performed Skewness and Kurtosis calculations on the dataset.

Skewness and Kurtosis Calculations

```
tab_ske_kur <- data_clean %>%
  dplyr::select(ends_with("_Subscore")) %>%
  psych::describe(ranges = FALSE)

skewness_kurtosis <- xtable::xtable(tab_ske_kur,
               digits = 3,
               label = "tab:Ske_Kur",
               caption="Skewness and Kurtosis Values for 8 Factors")

print(skewness_kurtosis, caption.placement = "top", comment=FALSE)
```

Table J.3

Skewness and Kurtosis Values for 8 Factors

	vars	n	mean	sd	skew	kurtosis	se
M_Subscore	1	330.000	4.935	0.986	-1.512	2.763	0.054
U_Subscore	2	330.000	4.621	1.042	-0.959	0.945	0.057
S_Subscore	3	330.000	5.039	0.909	-1.475	3.051	0.050
I_Subscore	4	330.000	4.461	1.011	-0.779	0.724	0.056
C_Subscore	5	330.000	5.338	0.674	-1.837	6.716	0.037
TP_Subscore	6	330.000	4.951	0.799	-0.958	1.709	0.044
SP_Subscore	7	330.000	4.223	1.037	-0.395	-0.050	0.057
CP_Subscore	8	330.000	4.549	0.902	-0.539	0.349	0.050

Interpretation of Skewness and Kurtosis

If the skewness is between -0.5 and 0.5 it is considered to be approximately symmetric. If it is between -1 and 1 it is considered to be moderately skewed. Greater than 1 or less than -1 is considered to be highly skewed. For Kurtosis, the Mesokurtic curve shape is ideal (or closest to the normal distribution) and is between -3 and 3. A kurtosis value greater than 3 indicates a Leptokurtic shape and a value less than 3 indicates a Platykurtic shape (McNeese, 2016).

Based upon these rules above, the following factors indicate an acceptable normal distribution: Social Presence (M = 4.22, SD = 1.04) was semi-normally distributed, with skewness of -0.39 (S.E. = 0.13) and kurtosis of -0.05 (S.E. = 0.27). Cognitive Presence (M = 4.55, SD = 0.90) was semi-normally distributed, with skewness of -0.54 (S.E. = 0.13) and kurtosis of 0.35 (S.E. = 0.27).

Some factors were moderately normal to a non-normal distribution and included: Usefulness (M = 4.62, SD = 1.04) was moderately distributed normally, with skewness of -0.96 (S.E. = 0.13) and kurtosis of 0.95 (S.E. = 0.27). Interest (M = 4.46, SD = 1.01) was moderately distributed normally, with skewness of -0.78 (S.E. = 0.13) and kurtosis of 0.72 (S.E. = 0.27). Teaching Presence (M = 4.95, SD = 0.80) was moderately distributed normally, with skewness of -0.96 (S.E. = 0.13) and kurtosis of 1.71 (S.E. = 0.27).

Three of the factors had skewness values less than one, indicating they were highly skewed and the kurtosis values were close to or greater than three, also indicating more of a Leptokurtic shape. eMpowerment (M = 4.94, SD = 0.99) was non-normally distributed with skewness of -1.51 (S.E. = 0.13) and kurtosis of 2.76 (S.E. = 0.27). Success (M = 5.04, SD = 0.91) was non-normally distributed with skewness of -1.48 (S.E. = 0.13) and kurtosis of 3.05 (S.E. = 0.27). Caring (M = 5.34, SD = 0.67) was non-normally distributed with skewness of -1.84 (S.E. = 0.13) and kurtosis of 6.72 (S.E. = 0.27).

Correlations

First, the researcher isolated the eight factor variables to create a new dataset that would be used to calculate the correlations. With that database a Correlogram was generated (see Figure J.9. Next, the researcher generated a correlation table of the learning environment and motivational factors (see Table J.4). Lastly, the researcher ran Intraclass Correlation (ICC) analysis with the 36 clusted course groups.

Correlogram of Learning Environment and Motivational Factors

Table 4.3 shows the results from the correlation analysis. Cohen suggests that d = 0.2 be considered a 'small' effect size, d = 0.5 represents a 'moderate' effect size and 0.8 a 'strong' effect size. As indicated by the table, there is a moderate to moderately-strong effect size for each of the eight factors with each other. This result means that the online learning environment and student motivation factors have a moderate to moderately-strong relationship with each other, which confirms the theoretical relationship between the personal and environment factors in the Triadic Reciprocal Causation theoretical framework from this study (Bandura, 1986).

Correlogram of Learning Environment and Motivational Factors

```
data_factors <- data_raw %>%
  dplyr::select(ends_with("_Subscore"))

cor(data_factors) %>%
  corrplot(cl.lim = c(0, 1),
           type = "upper",
           tl.col = "black",
           tl.srt = 45,
           col=colorRampPalette(c("black","white","black"))(100))
```

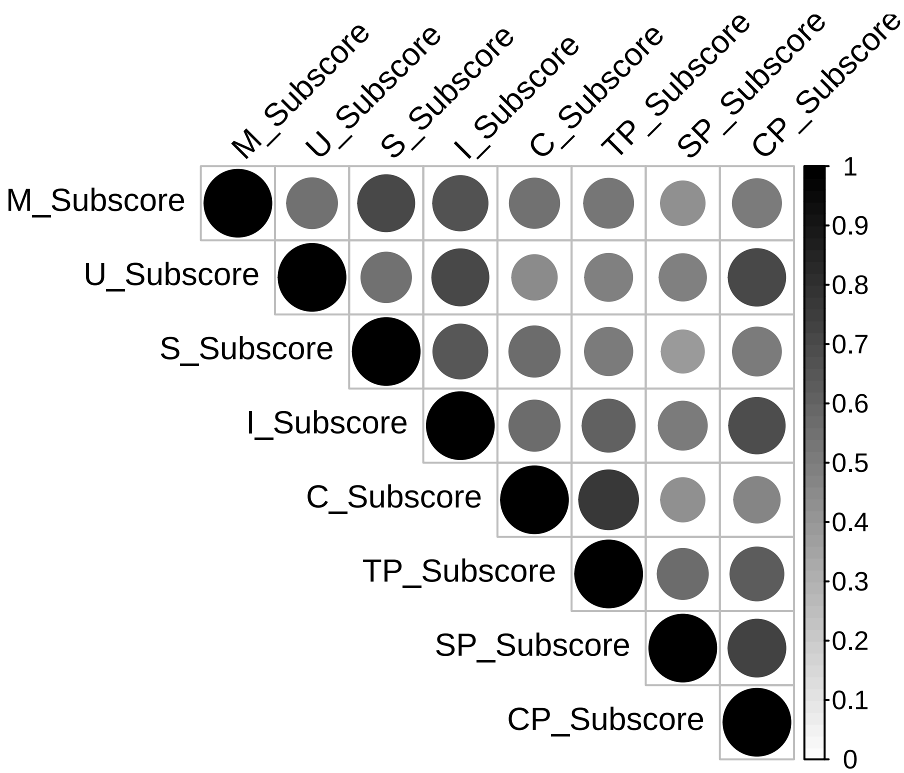

Figure J.9. Correlogram of Learning Environment and Motivational Factors

Correlation Table of Learning Environment and Motivational Factors

```
# Function retrieved from http://www.sthda.com/english/wiki/
#            elegant-correlation-table-using-xtable-r-package

# x is a matrix containing the data
# method : correlation method. "pearson"" or "spearman"" is supported
# removeTriangle : remove upper or lower triangle
# results :  if "html" or "latex"
  # the results will be displayed in html or latex format
corstars <- function(x, method=c("pearson", "spearman"),
                    removeTriangle=c("upper", "lower"),
                    result=c("none", "html", "latex")){
    #Compute correlation matrix
    require(Hmisc)
    x <- as.matrix(x)
    correlation_matrix<-rcorr(x, type=method[1])
    R <- correlation_matrix$r # Matrix of correlation coeficients
    p <- correlation_matrix$P # Matrix of p-value

    ## Define notions for significance levels; spacing is important.
    mystars <- ifelse(p < .0001, "****", ifelse(p < .001, "*** ",
       ifelse(p < .01, "**  ", ifelse(p < .05, "*   ", "    "))))

    ## trunctuate the correlation matrix to two decimal
    R <- format(round(cbind(rep(-1.11, ncol(x)), R), 2))[,-1]

    ## build a new matrix that includes the correlations with their
    ## apropriate stars
    Rnew <- matrix(paste(R, mystars, sep=""), ncol=ncol(x))
    diag(Rnew) <- paste(diag(R), " ", sep="")
    rownames(Rnew) <- colnames(x)
    colnames(Rnew) <- paste(colnames(x), "", sep="")

    ## remove upper triangle of correlation matrix
    if(removeTriangle[1]=="upper"){
      Rnew <- as.matrix(Rnew)
      Rnew[upper.tri(Rnew, diag = TRUE)] <- ""
      Rnew <- as.data.frame(Rnew)
    }

    ## remove lower triangle of correlation matrix
    else if(removeTriangle[1]=="lower"){
```

```
      Rnew <- as.matrix(Rnew)
      Rnew[lower.tri(Rnew, diag = TRUE)] <- ""
      Rnew <- as.data.frame(Rnew)
    }

    ## remove last column and return the correlation matrix
    Rnew <- cbind(Rnew[1:length(Rnew)-1])
    if (result[1]=="none") return(Rnew)
    else{
      if(result[1]=="html") print(xtable(Rnew), type="html")
      else print(xtable(Rnew, digits = 3,
                        label = "tab:cor_table",
                        caption="Correlation Table of Learning
                        Environment and Motivation Factors"),
                 type="latex",
                 comment=FALSE,
                 caption.placement = "top")
    }
}
```

```
corstars(data_factors, method = "pearson",
         removeTriangle = "upper", result = "latex")
```

Table J.4

Correlation Table of Learning Environment and Motivation Factors

	M_Subscore	U_Subscore	S_Subscore	I_Subscore	C_Subscore	TP_Subscore	SP_Subscore
M_Subscore							
U_Subscore	0.56****						
S_Subscore	0.70****	0.55****					
I_Subscore	0.66****	0.70****	0.65****				
C_Subscore	0.54****	0.44****	0.57****	0.56****			
TP_Subscore	0.54****	0.49****	0.50****	0.61****	0.77****		
SP_Subscore	0.43****	0.48****	0.40****	0.52****	0.42****	0.56****	
CP_Subscore	0.52****	0.71****	0.51****	0.69****	0.46****	0.63****	0.72****

Nesting and Intraclass Correlations

```
icc_stats <- statsBy(data_corr, group="CourseID")
print(icc_stats,short=FALSE)

FALSE Statistics within and between groups
FALSE Call: statsBy(data = data_corr, group = "CourseID")
FALSE Intraclass Correlation 1 (Percentage of variance due to groups)
FALSE    CourseID  M_Subscore  U_Subscore  S_Subscore  I_Subscore  C_Subscore
FALSE        1.00        0.07        0.14        0.04        0.13        0.03
FALSE TP_Subscore SP_Subscore CP_Subscore
FALSE        0.10        0.03        0.08
FALSE Intraclass Correlation 2 (Reliability of group differences)
FALSE    CourseID  M_Subscore  U_Subscore  S_Subscore  I_Subscore  C_Subscore
FALSE        1.00        0.40        0.60        0.26        0.58        0.23
FALSE TP_Subscore SP_Subscore CP_Subscore
FALSE        0.50        0.21        0.44
FALSE eta^2 between groups
FALSE  M_Subscore.bg  U_Subscore.bg  S_Subscore.bg  I_Subscore.bg  C_Subscore.bg
FALSE           0.17           0.23           0.14           0.22           0.13
FALSE TP_Subscore.bg SP_Subscore.bg CP_Subscore.bg
FALSE           0.19           0.13           0.17
FALSE Correlation between groups
FALSE               M_Sb. U_Sb. S_Sb. I_Sb. C_Sb. TP_S. SP_S. CP_S.
FALSE M_Subscore.bg  1.00
FALSE U_Subscore.bg  0.77  1.00
FALSE S_Subscore.bg  0.63  0.55  1.00
FALSE I_Subscore.bg  0.81  0.79  0.71  1.00
FALSE C_Subscore.bg  0.47  0.31  0.49  0.47  1.00
FALSE TP_Subscore.bg 0.68  0.52  0.57  0.67  0.85  1.00
```

```
FALSE SP_Subscore.bg 0.63  0.57  0.48  0.67  0.48  0.58  1.00
FALSE CP_Subscore.bg 0.81  0.80  0.61  0.78  0.46  0.66  0.82  1.00
FALSE Correlation within groups
FALSE                M_Sb. U_Sb. S_Sb. I_Sb. C_Sb. TP_S. SP_S. CP_S.
FALSE M_Subscore.wg  1.00
FALSE U_Subscore.wg  0.51  1.00
FALSE S_Subscore.wg  0.72  0.55  1.00
FALSE I_Subscore.wg  0.63  0.68  0.64  1.00
FALSE C_Subscore.wg  0.56  0.48  0.58  0.59  1.00
FALSE TP_Subscore.wg 0.51  0.49  0.49  0.59  0.76  1.00
FALSE SP_Subscore.wg 0.39  0.47  0.38  0.49  0.41  0.56  1.00
FALSE CP_Subscore.wg 0.46  0.70  0.50  0.67  0.46  0.62  0.71  1.00
FALSE
FALSE Many results are not shown directly. To see specific objects select from the following list:
FALSE  mean sd n F ICC1 ICC2 ci1 ci2 raw rbg ci.bg pbg rwg nw ci.wg pwg etabg etawg nwg nG Call
```

Interpretation of Intraclass Correlation (ICC) Tables

The sample of students in the study came from 36 different courses in eight different universities. A purely nested, 3-level model analyzing students within courses within universities was developed. Intraclass correlations (ICC) were calculated by analyzing the eight factors within course groups. Table 4.4 provides these results of the correlation among observations with the same course (Koo & Li, 2016). For each of the eight factors analyzed, the ICC (1) value, which is the percentage of variance due to the course, ranged between 3% - 14%. ICC (2) values which are less than .5 indicate poor reliability, between .5 and .75 are moderate, between .75 and .9 are good, and higher than .9 is excellent (Koo & Li, 2016) The reliability of course differences, or ICC (2), for three of the factors was moderate (Usefulness, Interest, and Teaching Presence), while all the other factors indicate a poor reliability of course differences. This finding indicates that while multilevel analyses will provide a little benefit over a single-level model with this particular study sample, it will not be a dramatic difference.

Interpretation of Correlation Tables

As indicated by Figure J.9 and Table J.4, there was a moderate to moderately-strong effect size for each of the eight factors with each other.

Survival Analysis

To perform the Survival Analysis, the researcher used R to generate Kaplan-Meier Plots of each of the eight factors. Then, the researcher developed Multilevel Cox Regression equations with each independent factor, all eight factors, and then used backward stepwise factor removal approach. This involved deleting the most statistically insignificant variable and continuing the process until the final model demonstrated the most significant values.

After a final model was selected, the researcher ran a likelihood-ratio test to measure if the 8-factor model and the 2-factor final model were similar or not. The final Multilevel Cox Regression Model summary was generated with the two selected variables and a visualization of the model was generated to help with interpretation of the analysis.

Kaplan-Meier Plots

The Kaplan-Meier Plots were used to visual the survival over a period of time. The timeline for this study was determined to be the Fall 2018 semester (116 days). The researcher created Kaplan-Meier plots for each of the eight factor variables by using the created tertile variables which separated the factors into “High”, “Medium”, and “Low” perception groups. The researcher also generated the quartile groups, but this data seemed to clutter up the figures. Therefore, the researcher determined that breaking up the groups into three equally divided groups was a better fit (see Figures J.10, J.11, J.12, J.13, J.14, J.15, J.16, J.17).

Kaplan-Meier Plot of eMpowerment

```
survfit(Surv(DaysPersisted, notCompleted) ~ M_Subscore_Tertile,
        data = data_clean) %>%
  autoplot(conf.int = FALSE,
           surv.linetype = c("strata")) +
  theme_bw() +
  labs(x = "Time, days",
       y = "Survival Probability",
       linetype = "eMpowerment Factor \n(scale 1-6)") +
  scale_linetype_discrete(breaks=c("High","Med","Low")) +
  theme(legend.background = element_rect(color = "black"),
        legend.position = c(0, 0),
        legend.justification = c(-0.1, -0.1),
        legend.key.width = unit(1.5, "cm")) +
  scale_color_manual(values=c("black","black","black")) +
  guides(color = FALSE)
```

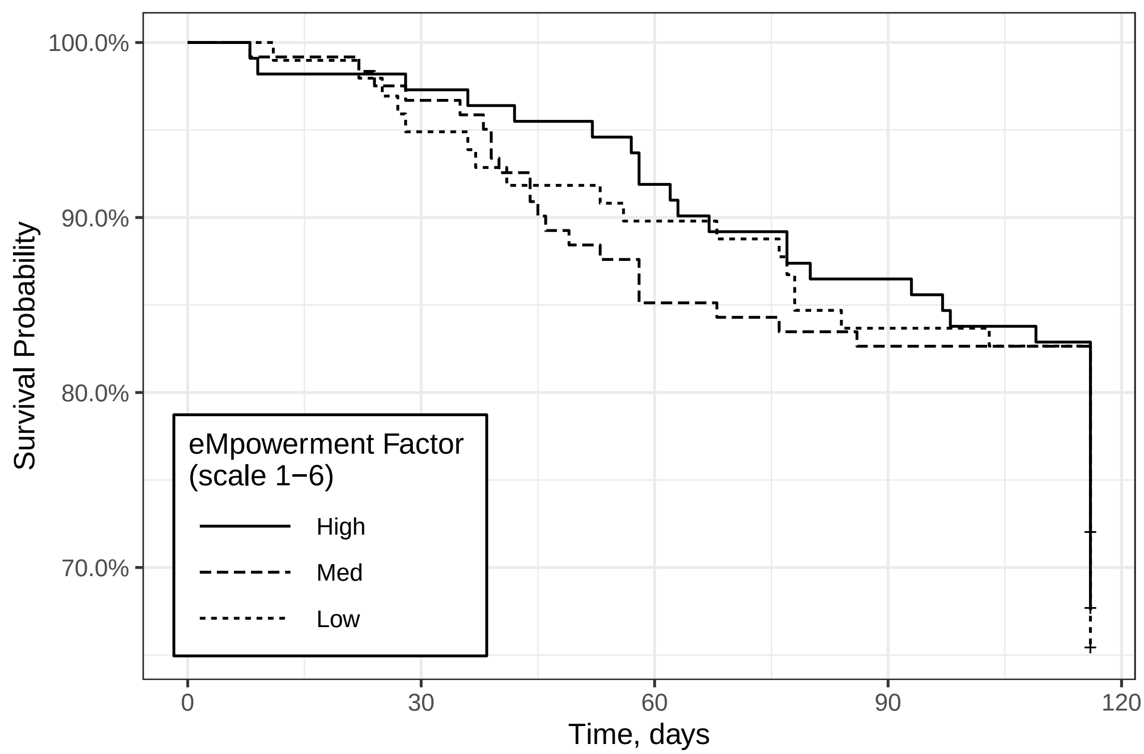

Figure J.10. Kaplan-Meier Plot of eMpowerment.

Kaplan-Meier Plot of Usefulness

```
survfit(Surv(DaysPersisted, notCompleted) ~ U_Subscore_Tertile,
        data = data_clean) %>%
  autoplot(conf.int = FALSE,
           surv.linetype = c("strata")) +
  theme_bw() +
  labs(x = "Time, days",
       y = "Survival Probability",
       linetype = "Usefulness Factor\nscale(1-6)") +
  scale_linetype_discrete(breaks=c("High","Med","Low")) +
  theme(legend.background = element_rect(color = "black"),
        legend.position = c(0, 0),
        legend.justification = c(-0.1, -0.1),
        legend.key.width = unit(1.5, "cm")) +
  scale_color_manual(values=c("black","black","black")) +
  guides(color = FALSE)
```

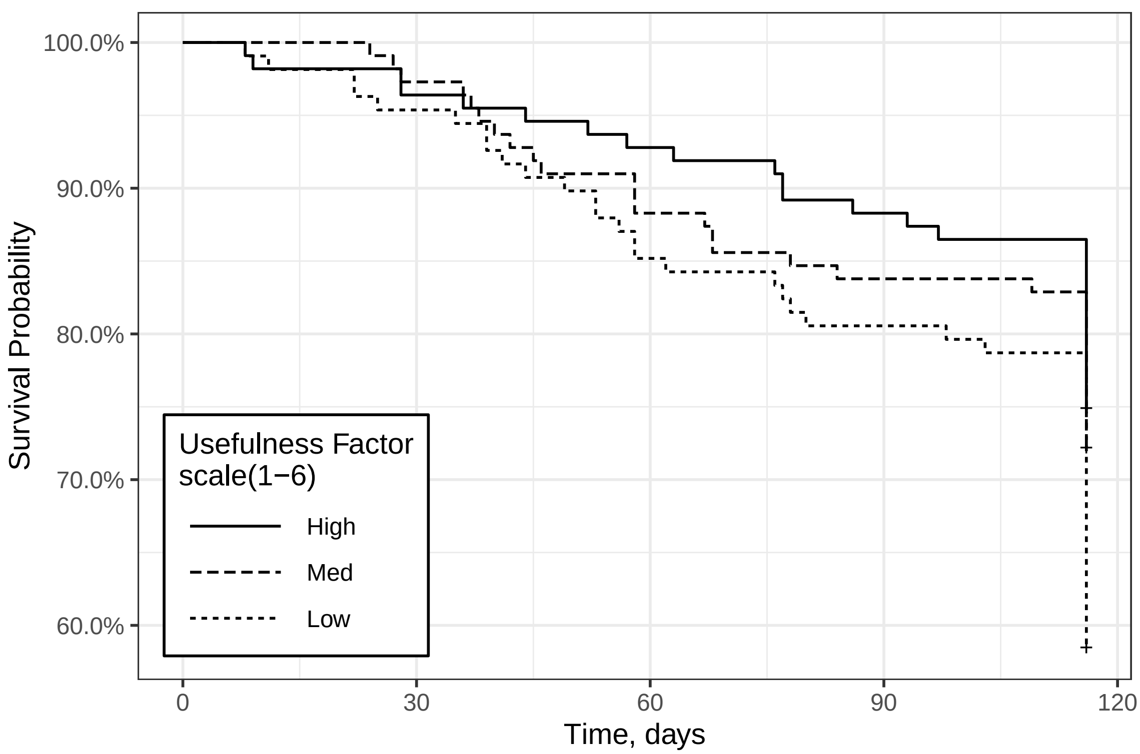

Figure J.11. Kaplan-Meier Plot of Usefulness.

Kaplan-Meier Plot of Success

```
survfit(Surv(DaysPersisted, notCompleted) ~ S_Subscore_Tertile,
        data = data_clean) %>%
  autoplot(conf.int = FALSE,
           surv.linetype = c("strata")) +
  theme_bw() +
  labs(x = "Time, days",
       y = "Survival Probability",
       linetype = "Success Factor\nscale(1-6)") +
  scale_linetype_discrete(breaks=c("High","Med","Low")) +
  theme(legend.background = element_rect(color = "black"),
        legend.position = c(0, 0),
        legend.justification = c(-0.1, -0.1),
        legend.key.width = unit(1.5, "cm")) +
  scale_color_manual(values=c("black","black","black")) +
  guides(color = FALSE)
```

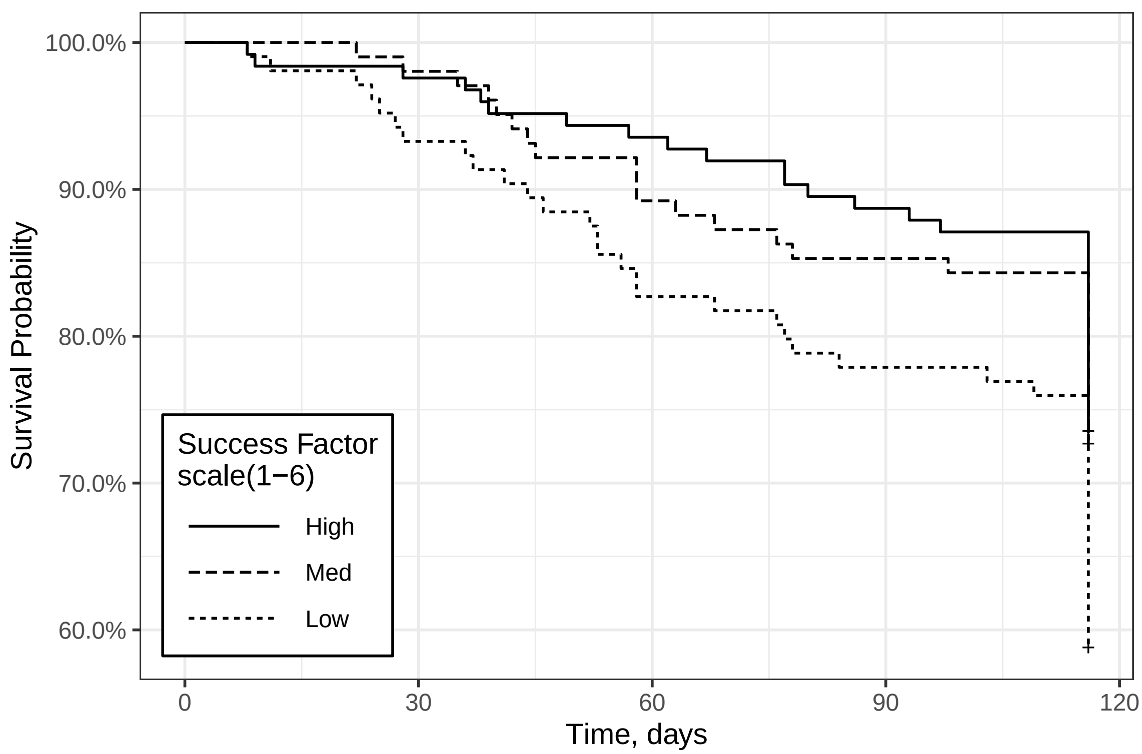

Figure J.12. Kaplan-Meier Plot of Success.

Kaplan-Meier Plot of Interest

```
survfit(Surv(DaysPersisted, notCompleted) ~ I_Subscore_Tertile,
        data = data_clean) %>%
  autoplot(conf.int = FALSE,
           surv.linetype = c("strata")) +
  theme_bw() +
  labs(x = "Time, days",
       y = "Survival Probability",
       linetype = "Interest Factor\nscale(1-6)") +
  scale_linetype_discrete(breaks=c("High","Med","Low")) +
  theme(legend.background = element_rect(color = "black"),
        legend.position = c(0, 0),
        legend.justification = c(-0.1, -0.1),
        legend.key.width = unit(1.5, "cm")) +
  scale_color_manual(values=c("black","black","black")) +
  guides(color = FALSE)
```

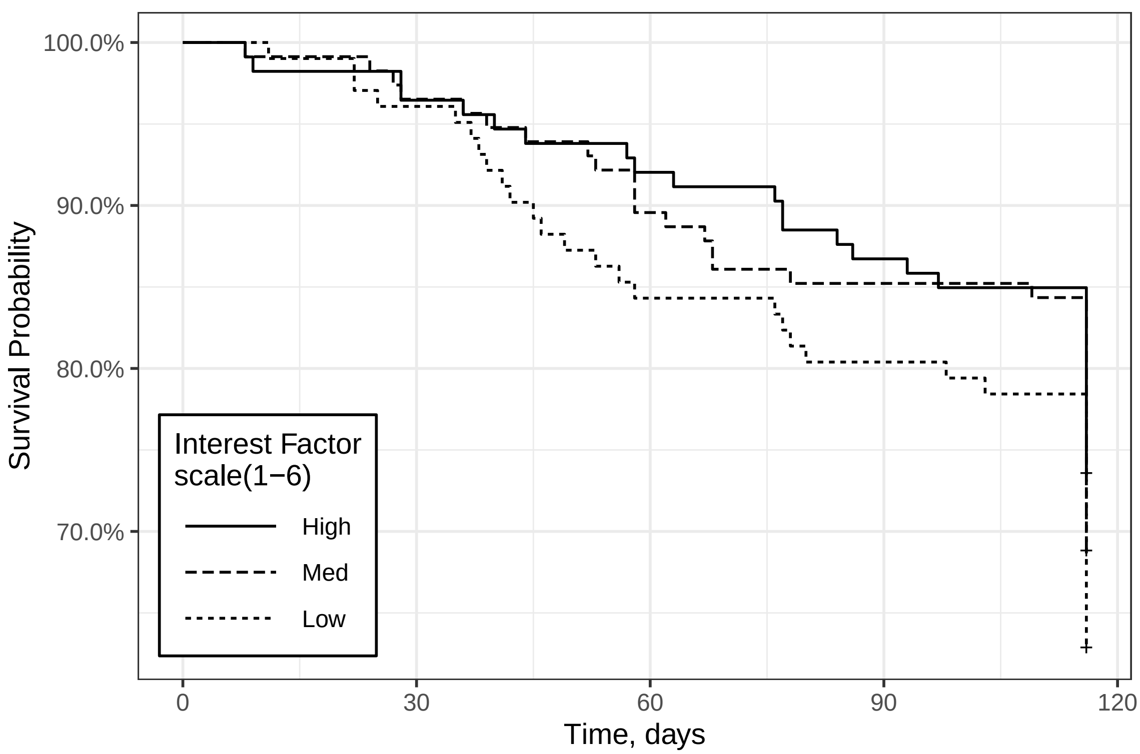

Figure J.13. Kaplan-Meier Plot of Interest.

Kaplan-Meier Plot of Care

```
survfit(Surv(DaysPersisted, notCompleted) ~ C_Subscore_Tertile,
        data = data_clean) %>%
  autoplot(conf.int = FALSE,
           surv.linetype = c("strata")) +
  theme_bw() +
  labs(x = "Time, days",
       y = "Survival Probability",
       linetype = "Care Factor\nscale(1-6)") +
  scale_linetype_discrete(breaks=c("High","Med","Low")) +
  theme(legend.background = element_rect(color = "black"),
        legend.position = c(0, 0),
        legend.justification = c(-0.1, -0.1),
        legend.key.width = unit(1.5, "cm")) +
  scale_color_manual(values=c("black","black","black")) +
  guides(color = FALSE)
```

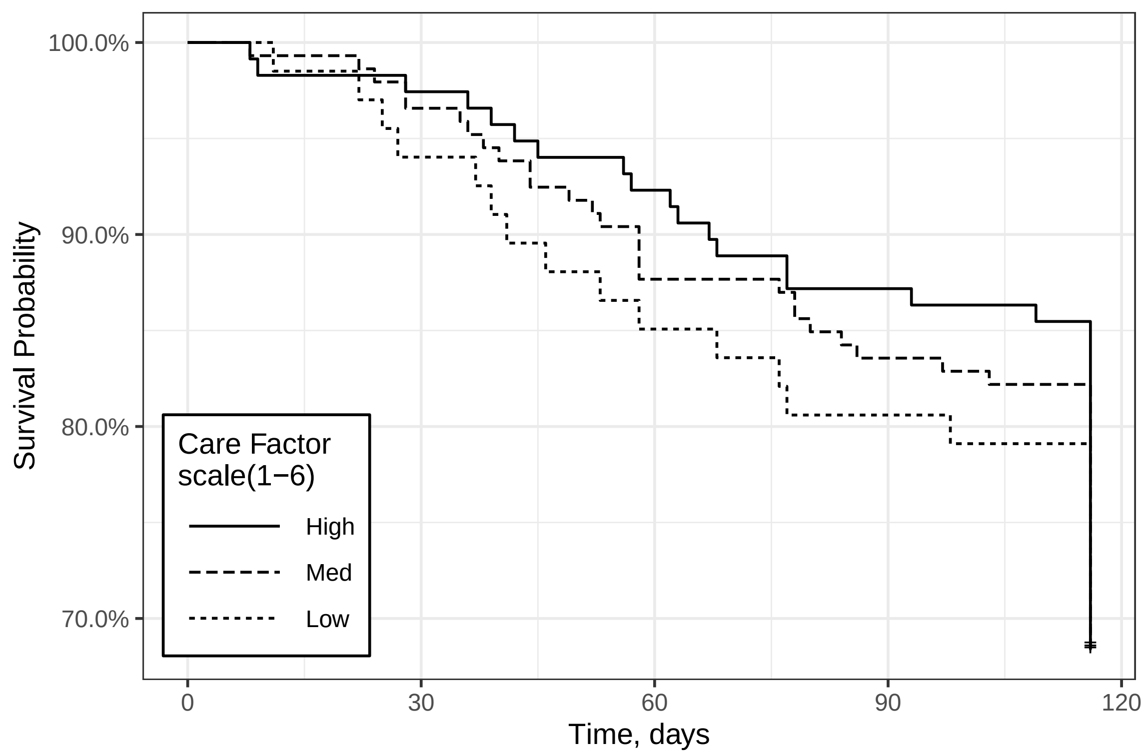

Figure J.14. Kaplan-Meier Plot of Care.

Kaplan-Meier Plot of Teaching Presence

```
survfit(Surv(DaysPersisted, notCompleted) ~ TP_Subscore_Tertile,
        data = data_clean) %>%
  autoplot(conf.int = FALSE,
           surv.linetype = c("strata")) +
  theme_bw() +
  labs(x = "Time, days",
       y = "Survival Probability",
       linetype = "Teaching Presence Factor\nscale(1-6)") +
  scale_linetype_discrete(breaks=c("High","Med","Low")) +
  theme(legend.background = element_rect(color = "black"),
        legend.position = c(0, 0),
        legend.justification = c(-0.1, -0.1),
        legend.key.width = unit(1.5, "cm")) +
  scale_color_manual(values=c("black","black","black")) +
  guides(color = FALSE)
```

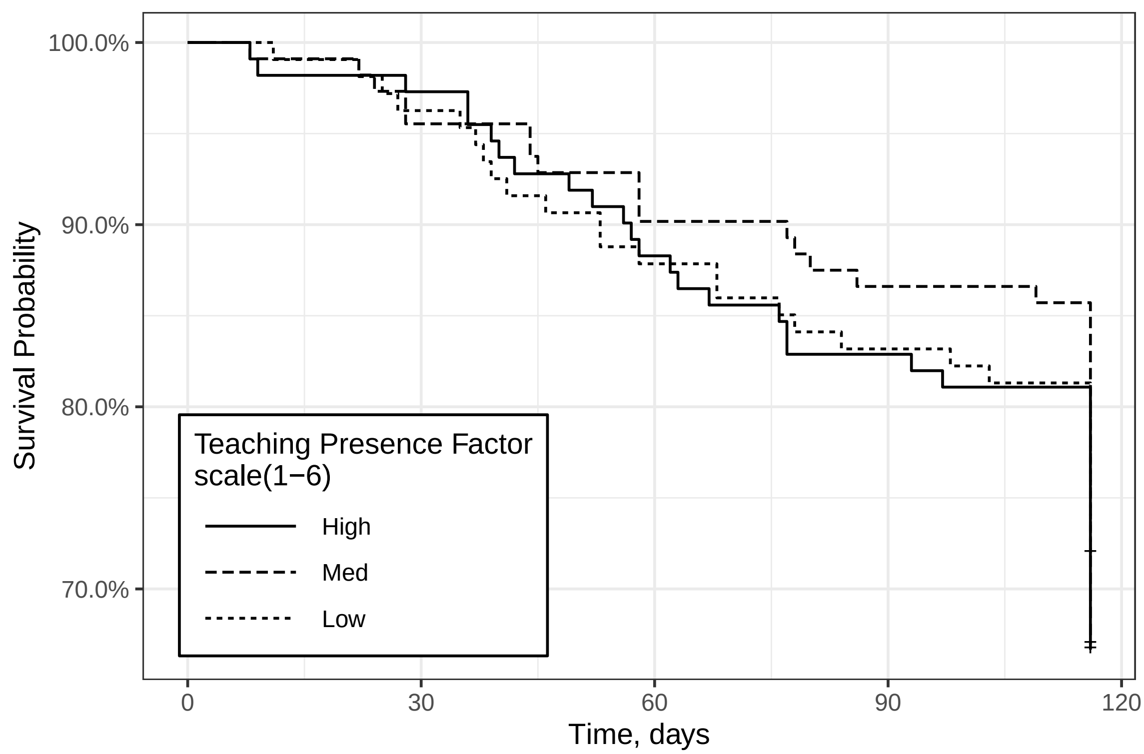

Figure J.15. Kaplan-Meier Plot of Teaching Presence.

Kaplan-Meier Plot of Social Presence

```
survfit(Surv(DaysPersisted, notCompleted) ~ SP_Subscore_Tertile,
        data = data_clean) %>%
  autoplot(conf.int = FALSE,
           surv.linetype = c("strata")) +
  theme_bw() +
  labs(x = "Time, days",
       y = "Survival Probability",
       linetype = "Social Presence Factor\nscale(1-6)") +
  scale_linetype_discrete(breaks=c("High","Med","Low")) +
  theme(legend.background = element_rect(color = "black"),
        legend.position = c(0, 0),
        legend.justification = c(-0.1, -0.1),
        legend.key.width = unit(1.5, "cm")) +
  scale_color_manual(values=c("black","black","black")) +
  guides(color = FALSE)
```

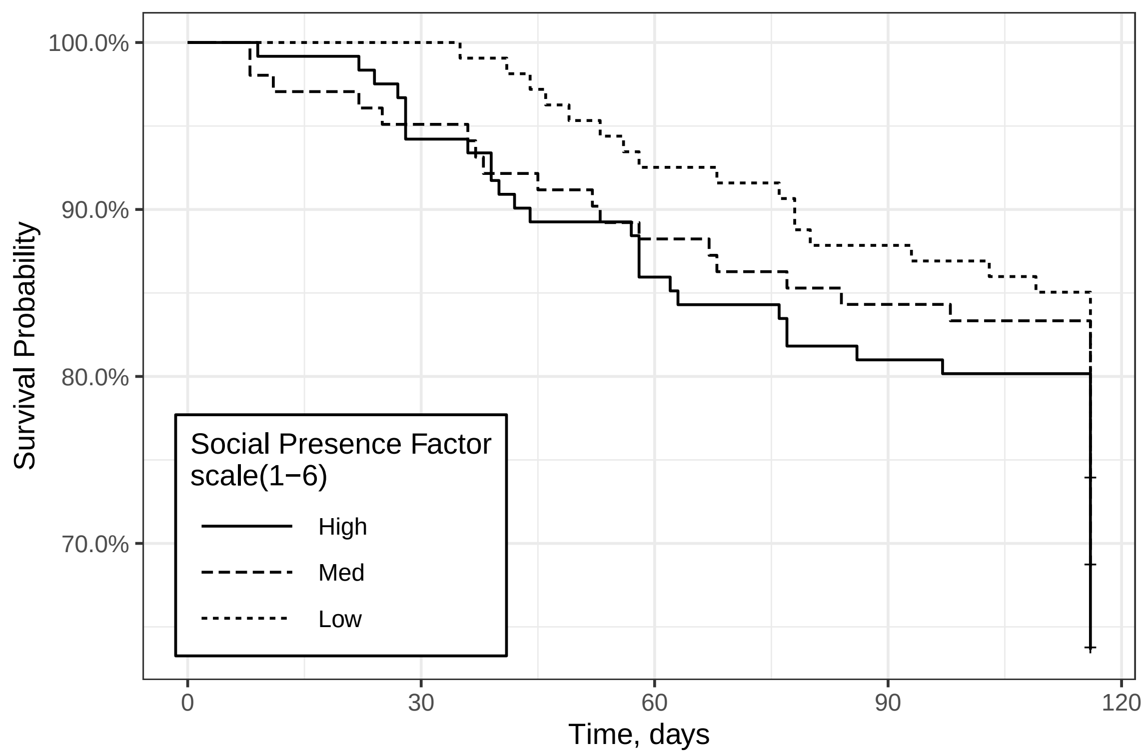

Figure J.16. Kaplan-Meier Plot of Social Presence.

Kaplan-Meier Plot of Cognitive Presence

```
survfit(Surv(DaysPersisted, notCompleted) ~ CP_Subscore_Tertile,
        data = data_clean) %>%
  autoplot(conf.int = FALSE,
           surv.linetype = c("strata")) +
  theme_bw() +
  labs(x = "Time, days",
       y = "Survival Probability",
       linetype = "Cognitive Presence Factor\nscale(1-6)") +
  scale_linetype_discrete(breaks=c("High","Med","Low")) +
  theme(legend.background = element_rect(color = "black"),
        legend.position = c(0, 0),
        legend.justification = c(-0.1, -0.1),
        legend.key.width = unit(1.5, "cm")) +
  scale_color_manual(values=c("black","black","black")) +
  guides(color = FALSE)
```

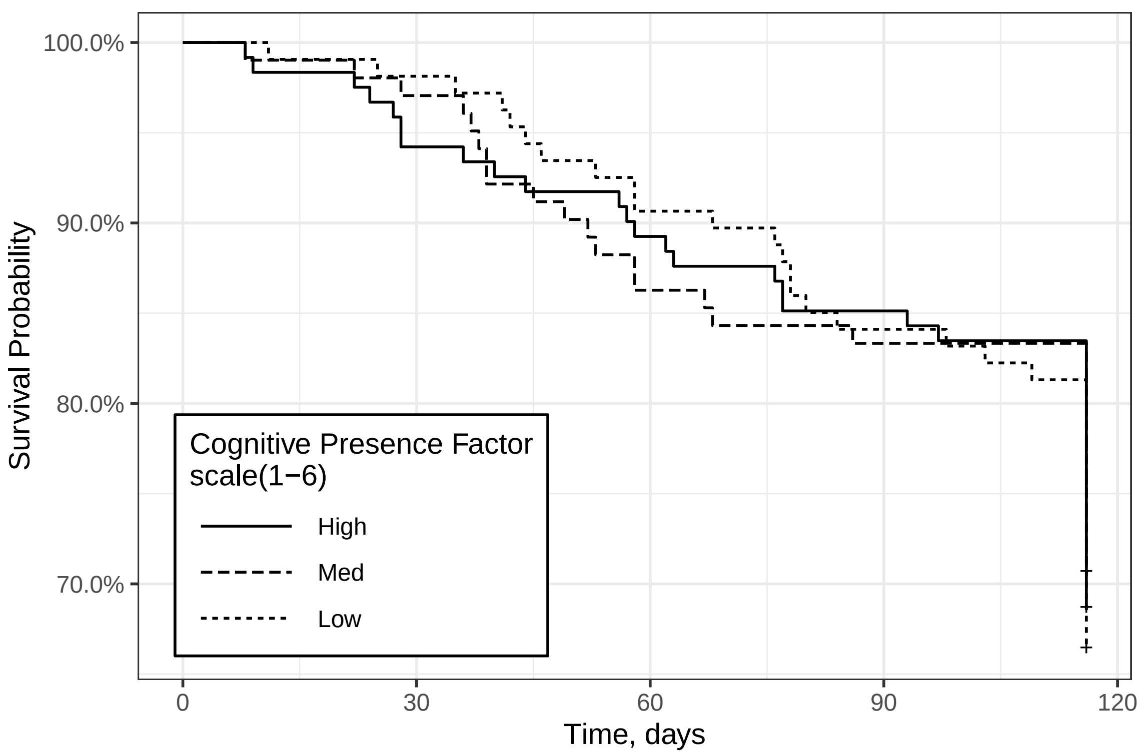

Figure J.17. Kaplan-Meier Plot of Cognitive Presence.

Interpretation of Kaplan-Meier Plots

Of the eight Kaplan-Meier plots generated, the most promising ones included Success (see Figure J.12), and Social Presence (see Figure J.16). Contrary to the behavior of the Success factor on course persistence, the Social Presence Kaplan-Meier plot showed that students in the high perception group had less time-to-event compared to the students in the low perception group. More about this particular behavior was analyzed in the Multilevel Cox Regression.

Multilevel Cox Regression

After analyzing the Kaplan-Meier plots, the researcher then generated Multilevel Cox Regression models for each of the eight variables (see Tables J.5 and J.6), and then started with the complete 8-factor model and used backward stepwise factor removal process to get to the final 2-factor model (see Tables J.7 and J.8). A final summary table was then generated (see Table J.10) and a visualization to represent the final model (see Figure J.18).

R Multilevel Cox Regression Formulas

The researcher generated the Multilevel Cox Regression tables using the following commands in R:

```
cox_M <- coxme(Surv(DaysPersisted, notCompleted) ~ M_Subscore +
                (1 | SchoolID/CourseID), data = data_clean)

cox_U <- coxme(Surv(DaysPersisted, notCompleted) ~ U_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_S <- coxme(Surv(DaysPersisted, notCompleted) ~ S_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_I <- coxme(Surv(DaysPersisted, notCompleted) ~ I_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_C <- coxme(Surv(DaysPersisted, notCompleted) ~ C_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_TP <- coxme(Surv(DaysPersisted, notCompleted) ~ TP_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_SP <- coxme(Surv(DaysPersisted, notCompleted) ~ SP_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_CP <- coxme(Surv(DaysPersisted, notCompleted) ~ CP_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_all <- coxme(formula = Surv(DaysPersisted, notCompleted) ~
                 M_Subscore + U_Subscore + S_Subscore +
                 I_Subscore + C_Subscore + TP_Subscore +
                 SP_Subscore + CP_Subscore +
                 (1 | SchoolID/CourseID), data = data_clean)
```

```
cox_7 <- coxme(formula = Surv(DaysPersisted, notCompleted) ~
               M_Subscore + U_Subscore + S_Subscore +
               I_Subscore + TP_Subscore + SP_Subscore +
               CP_Subscore + (1 | SchoolID/CourseID),
               data = data_clean)

cox_6 <- coxme(formula = Surv(DaysPersisted, notCompleted) ~
               M_Subscore + U_Subscore + S_Subscore +
               I_Subscore + SP_Subscore + CP_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_5 <- coxme(formula = Surv(DaysPersisted, notCompleted) ~
               M_Subscore + U_Subscore + S_Subscore +
               I_Subscore + SP_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_4 <- coxme(formula = Surv(DaysPersisted, notCompleted) ~
               U_Subscore + S_Subscore + I_Subscore +
               SP_Subscore + (1 | SchoolID/CourseID),
               data = data_clean)

cox_3 <- coxme(formula = Surv(DaysPersisted, notCompleted) ~
               U_Subscore + S_Subscore + SP_Subscore +
               (1 | SchoolID/CourseID), data = data_clean)

cox_final <- coxme(Surv(DaysPersisted, notCompleted) ~
                   S_Subscore + SP_Subscore +
                   (1 | SchoolID/CourseID), data = data_clean)

cox_interaction <-  coxme(Surv(DaysPersisted, notCompleted) ~
                   S_Subscore*SP_Subscore + (1 | SchoolID/CourseID),
                   data = data_clean)
```

Multilevel Cox Regression Extraction Functions

```
extract_coxme_reg <- function (model,
                               include.aic = TRUE,
                               include.bic = TRUE,
                               include.loglik = TRUE,
                               include.deviance = FALSE,
                               include.nobs = TRUE,
                               ...) {

  s <- summary(model, ...)
  coefficient.names <- names(s$coef)
  coefficients <- fixef(model)
  co_exp = exp(coefficients)

  nvar <- length(coefficients)
  nfrail <- nrow(model$variance) - nvar

  standard.errors <- sqrt(diag(as.matrix(model$variance))[nfrail +
                                                           1:nvar])
  z <- coefficients/standard.errors
  significance <- 2*(1-pnorm(abs(z)))

  ci.l <- exp(coefficients - 1.96*standard.errors)
  ci.u <- exp(coefficients + 1.96*standard.errors)

  aic <- AIC(model)
  bic <- BIC(model)
  lik <- logLik(model)[1]
  n <- dim(model.frame(model))[1]
  gof <- numeric()
  gof.names <- character()
  gof.decimal <- logical()

  if (include.aic == TRUE) {
    gof <- c(gof, aic)
    gof.names <- c(gof.names, "AIC")
    gof.decimal <- c(gof.decimal, TRUE)
  }
  if (include.bic == TRUE) {
    gof <- c(gof, bic)
    gof.names <- c(gof.names, "BIC")
    gof.decimal <- c(gof.decimal, TRUE)
```

```
  }
  if (include.loglik == TRUE) {
    gof <- c(gof, lik)
    gof.names <- c(gof.names, "Log Likelihood")
    gof.decimal <- c(gof.decimal, TRUE)
  }
  if (include.deviance == TRUE) {
    gof <- c(gof, dev)
    gof.names <- c(gof.names, "Deviance")
    gof.decimal <- c(gof.decimal, TRUE)
  }
  if (include.nobs == TRUE) {
    gof <- c(gof, n)
    gof.names <- c(gof.names, "Num. obs.")
    gof.decimal <- c(gof.decimal, FALSE)
  }

  tr <- createTexreg(coef.names = coefficient.names,
                     coef = coefficients,
                     se = standard.errors,
                     pvalues = significance,
                     gof.names = gof.names,
                     gof = gof,
                     gof.decimal = gof.decimal)
  return(tr)
}
# Function by Sarah Schwartz: http://www.sarahschwartzstats.com/
```

Table J.5

Multilevel Cox Regression Models for Independent Factors of eMpowerment, Usefulness, Success, and Interest

	M	U	S	I
M_Subscore	-0.037			
	(0.094)			
U_Subscore		-0.147		
		(0.091)		
S_Subscore			-0.213^{*}	
			(0.098)	
I_Subscore				-0.140
				(0.097)
AIC	1153.592	1151.521	1149.878	1152.044
BIC	1183.734	1179.678	1178.113	1181.490
Log Likelihood	-565.398	-565.113	-564.261	-564.887
Num. obs.	330	330	330	330

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Tables of Multilevel Cox Regression Models

```
texreg::texreg(list(coxme_M, coxme_U, coxme_S, coxme_I),
               custom.model.names = c("M", "U", "S", "I"),
               digits = 3,
               label = "tab:M_U_S_I",
               caption="Multilevel Cox Regression Models for
               Independent Factors of eMpowerment, Usefulness,
               Success, and Interest",
               caption.above = TRUE)
```

Table J.6

Multilevel Cox Regression Models for Independent Factors of Care, Teaching Presence, Social Presence, and Cognitive Presence

	C	TP	SP	CP
C_Subscore	-0.065			
	(0.142)			
TP_Subscore		0.080		
		(0.130)		
SP_Subscore			0.227^{*}	
			(0.105)	
CP_Subscore				-0.020
				(0.115)
AIC	1153.461	1153.080	1148.287	1153.596
BIC	1183.581	1184.349	1181.140	1183.976
Log Likelihood	-565.340	-564.716	-561.719	-565.309
Num. obs.	330	330	330	330

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

```
texreg::texreg(list(coxme_C, coxme_TP, coxme_SP, coxme_CP),
               custom.model.names = c("C", "TP", "SP", "CP"),
               digits = 3,
               label = "tab:C_TP_SP_CP",
               caption="Multilevel Cox Regression Models for
               Independent Factors of Care, Teaching Presence,
               Social Presence, and Cognitive Presence",
               caption.above = TRUE)
```

```
texreg::texreg(list(coxme_all, coxme_7, coxme_6, coxme_5),
               custom.model.names = c("Full", "7", "6", "5"),
               digits = 3,
               label = "tab:all_7_6_5",
               caption="Multilevel Cox Regression Models for 8,
               7, 6, and 5 Factors by Removal",
               caption.above = TRUE)
```

Table J.7

Multilevel Cox Regression Models for 8, 7, 6, and 5 Factors by Removal

	Full	7	6	5
M_Subscore	0.196	0.176	0.193	0.197
	(0.158)	(0.154)	(0.151)	(0.152)
U_Subscore	−0.155	−0.152	−0.158	−0.195
	(0.146)	(0.144)	(0.144)	(0.130)
S_Subscore	−0.307	-0.326^{*}	-0.327^{*}	-0.321^{*}
	(0.166)	(0.162)	(0.162)	(0.163)
I_Subscore	−0.089	−0.100	−0.089	−0.114
	(0.164)	(0.164)	(0.164)	(0.159)
C_Subscore	−0.172			
	(0.246)			
TP_Subscore	0.188	0.098		
	(0.214)	(0.169)		
SP_Subscore	0.444^{**}	0.438^{**}	0.457^{**}	0.405^{***}
	(0.153)	(0.152)	(0.149)	(0.121)
CP_Subscore	−0.170	−0.150	−0.125	
	(0.205)	(0.204)	(0.200)	
AIC	1146.330	1144.997	1143.435	1141.908
BIC	1195.560	1191.748	1187.610	1183.676
Log Likelihood	-554.548	-554.819	-555.012	-555.159
Num. obs.	330	330	330	330

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table J.8

Multilevel Cox Regression Models for 4, 3, and 2 Factors by Removal and Interaction Model

	4	3	Final	Interaction
U_Subscore	-0.184	-0.204		
	(0.131)	(0.119)		
S_Subscore	-0.225	-0.250^{*}	-0.356^{**}	-0.690^{**}
	(0.143)	(0.125)	(0.109)	(0.243)
I_Subscore	-0.056			
	(0.154)			
SP_Subscore	0.423^{***}	0.416^{***}	0.353^{**}	-0.051
	(0.120)	(0.119)	(0.112)	(0.295)
S_Subscore:SP_Subscore				0.088
				(0.060)
AIC	1141.974	1140.181	1141.005	1140.884
BIC	1180.238	1175.591	1174.966	1177.272
Log Likelihood	-556.518	-556.700	-557.660	-556.681
Num. obs.	330	330	330	330

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

```
texreg::texreg(list(coxme_4, coxme_3, coxme_final,
                    coxme_interaction),
               custom.model.names = c("4", "3", "Final",
                                      "Interaction"),
               digits = 3,
               label = "tab:4_3_final_interaction",
               caption="Multilevel Cox Regression Models for 4,
               3, and 2 Factors by Removal and Interaction Model",
               caption.above = TRUE)
```

Final Multilevel Cox Regression Model Analysis

A likelihood-ration test was performed between the 8-factor full model and the 2-factor final model to see if there is a significant better fit of using the full model instead of the reduced factor model. The likelihood-ratio test showed that the 8-factor model does NOT fit better than the 2-factor model (see Table J.11). Therefore, using the 2-factor model was appropriate for this analysis.

```
comp_anova <- xtable::xtable(anova(cox_all, cox_final),
               digits = 3,
               label = "tab:Likelihood",
               caption="Analysis of Deviance Table Between 8-Factor
               Full Model and 2-Factor Final Model")

print(comp_anova, caption.placement = "top", comment=FALSE)
```

Table J.9

Analysis of Deviance Table Between 8-Factor Full Model and 2-Factor Final Model

	loglik	Chisq	Df	P(>|Chi|)
1	-567.979			
2	-570.923	5.889	6.000	0.436

Building Final Multilevel Cox Regression Table

```
extract_coxme_exp <- function (model,
                               include.aic = TRUE,
                               include.bic = TRUE,
                               include.loglik = TRUE,
                               include.deviance = FALSE,
                               include.nobs = TRUE,
                               ...) {

  s <- summary(model, ...)
  coefficient.names <- names(s$coef)
  coefficients <- fixef(model)
  co_exp = exp(coefficients)

  nvar <- length(coefficients)
  nfrail <- nrow(model$variance) - nvar

  standard.errors <- sqrt(diag(as.matrix(model$variance))[nfrail +
                                                               1:nvar])
  z <- coefficients/standard.errors
  significance <- 2*(1-pnorm(abs(z)))

  ci.l <- exp(coefficients - 1.96*standard.errors)
  ci.u <- exp(coefficients + 1.96*standard.errors)

  aic <- AIC(model)
  bic <- BIC(model)
  lik <- logLik(model)[1]
  n <- dim(model.frame(model))[1]
  gof <- numeric()
  gof.names <- character()
  gof.decimal <- logical()

  if (include.aic == TRUE) {
    gof <- c(gof, aic)
    gof.names <- c(gof.names, "AIC")
    gof.decimal <- c(gof.decimal, TRUE)
  }
  if (include.bic == TRUE) {
    gof <- c(gof, bic)
    gof.names <- c(gof.names, "BIC")
    gof.decimal <- c(gof.decimal, TRUE)
```

```
  }
  if (include.loglik == TRUE) {
    gof <- c(gof, lik)
    gof.names <- c(gof.names, "Log Likelihood")
    gof.decimal <- c(gof.decimal, TRUE)
  }
  if (include.deviance == TRUE) {
    gof <- c(gof, dev)
    gof.names <- c(gof.names, "Deviance")
    gof.decimal <- c(gof.decimal, TRUE)
  }
  if (include.nobs == TRUE) {
    gof <- c(gof, n)
    gof.names <- c(gof.names, "Num. obs.")
    gof.decimal <- c(gof.decimal, FALSE)
  }

  tr <- createTexreg(coef.names = coefficient.names,
                     coef = co_exp,
                     ci.low = ci.l,
                     ci.up = ci.u,
                     pvalues = significance,
                     gof.names = gof.names,
                     gof = gof,
                     gof.decimal = gof.decimal)
  return(tr)
}
# Function by Sarah Schwartz: http://www.sarahschwartzstats.com/

texreg::texreg(extract_coxme_exp(cox_final),
               custom.model.names = "HR, Not Completing Course",
               caption = "Multilevel Cox Regression Results",
               caption.above = TRUE,
               label = "tab:cox_reg_final",
               ci.test = 1,
               digits = 3,
               float.pos = "hb",
               single.row = TRUE)
```

Cox mixed-effects model fit by maximum likelihood Data: data_clean events, n = 104, 330 Iterations= 15 79 NULL Integrated Fitted Log-likelihood -584.8488 -570.9229 -557.6597

```
Chisq    df           p    AIC    BIC
```

Integrated loglik 27.85 4.00 1.3366e-05 19.85 9.27 Penalized loglik 54.38 12.84 4.5941e-07 28.69 -5.27

Model: Surv(DaysPersisted, notCompleted) ~ S_Subscore + SP_Subscore + (1 | SchoolID/CourseID) Fixed coefficients coef exp(coef) se(coef) z p S_Subscore -0.3561781 0.7003479 0.1092492 -3.26 0.0011 SP_Subscore 0.3527880 1.4230294 0.1118656 3.15 0.0016

Random effects Group Variable Std Dev Variance SchoolID/CourseID (Intercept) 0.3688327 0.1360376 SchoolID (Intercept) 0.4331028 0.1875781

Table J.10

Multilevel Cox Regression Results

	HR, Not Completing Course
S_Subscore	0.700 [0.565; 0.868]*
SP_Subscore	1.423 [1.143; 1.772]*
AIC	1141.005
BIC	1174.966
Log Likelihood	-557.660
Num. obs.	330

* 1 outside the confidence interval

Multilevel Cox Regression – Comparing 'coxph' and 'coxme' Functions

```
cox_final_reg <- coxph(Surv(DaysPersisted, notCompleted) ~
                   S_Subscore + SP_Subscore, data = data_clean)

cox_final_cluster <- coxph(Surv(DaysPersisted, notCompleted) ~
                   S_Subscore + SP_Subscore + cluster(SchoolID),
                   data = data_clean)

cox_anova <- xtable::xtable(anova(cox_final_reg, cox_final),
               digits = 3,
               label = "tab:Likelihood",
               caption="Analysis of Deviance Table Between Regular
               Cox Regression and Frailty Model with Different
               Universities")

print(cox_anova, caption.placement = "top", comment=FALSE)
```

Table J.11

Analysis of Deviance Table Between Regular Cox Regression and Frailty Model with Different Universities

	loglik	Chisq	Df	P(>|Chi|)
1	-577.236			
2	-570.923	12.625	2.000	0.002

```
extract_cox_exp <- function(fit_cox){
  beta   = coef(fit_cox)
  betaci = confint(fit_cox)
  fit_cox_exp        = texreg::extract(fit_cox)
  fit_cox_exp@coef   = exp(beta)
  fit_cox_exp@ci.low = exp(betaci[, 1])
  fit_cox_exp@ci.up  = exp(betaci[, 2])
  return(fit_cox_exp)
}
# Function by Sarah Schwartz: http://www.sarahschwartzstats.com/

cox_print1 <- extract_cox_exp(cox_final_reg)
cox_print2 <- extract_cox_exp(cox_final_cluster)
cox_print3 <- extract_coxme_exp(cox_final)
```

Cox mixed-effects model fit by maximum likelihood Data: data_clean events, n = 104, 330 Iterations= 15 79 NULL Integrated Fitted Log-likelihood -584.8488 -570.9229 -557.6597

```
               Chisq    df           p   AIC   BIC
```

Integrated loglik 27.85 4.00 1.3366e-05 19.85 9.27 Penalized loglik 54.38 12.84 4.5941e-07 28.69 -5.27

Model: Surv(DaysPersisted, notCompleted) ~ S_Subscore + SP_Subscore + (1 | SchoolID/CourseID) Fixed coefficients coef exp(coef) se(coef) z p S_Subscore -0.3561781 0.7003479 0.1092492 -3.26 0.0011 SP_Subscore 0.3527880 1.4230294 0.1118656 3.15 0.0016

Random effects Group Variable Std Dev Variance SchoolID/CourseID (Intercept) 0.3688327 0.1360376 SchoolID (Intercept) 0.4331028 0.1875781

```
texreg::texreg(list(cox_print1, cox_print2, cox_print3),
               custom.model.names = c("coxph (no cluster)",
                                      "coxph (with cluster)",
                                      "coxme"),
               digits = 3,
               label = "tab:comparing_cox",
               caption="Comparing Multilevel Cox Regression Models",
               caption.above = TRUE)
```

Table J.12

Comparing Multilevel Cox Regression Models

	coxph (no cluster)	coxph (with cluster)	coxme
S_Subscore	0.678*	0.678*	0.700*
	[0.555; 0.828]	[0.601; 0.765]	[0.565; 0.868]
SP_Subscore	1.339*	1.339*	1.423*
	[1.093; 1.640]	[1.141; 1.571]	[1.143; 1.772]
AIC	1158.471	1158.471	1141.005
R^2	0.045	0.045	
Max. R^2	0.971	0.971	
Num. events	104	104	
Num. obs.	330	330	330
Missings	0	0	
PH test	0.574	0.574	
BIC			1174.966
Log Likelihood			-557.660

* 0 outside the confidence interval

Interpretation of Cox Regression Models

The researcher analyzed a three different Cox Regression models. (1) coxph without taking nesting into consideration, (2) coxph with using the clustering feature and (3) using the coxme function. Table J.10 shows a comparison of these three different functions. An anova comparison between coxph and coxme also showed there was a significant difference between the two models ($p < .01$). This indicated the importance of building a multilevel model.

Final Hazard Ratio Visualization

```
data_clean %>%
  dplyr::select(S_Subscore, SP_Subscore) %>%
  summary()
```

```
##    S_Subscore     SP_Subscore
##  Min.   :1.000   Min.   :1.000
##  1st Qu.:4.750   1st Qu.:3.556
##  Median :5.000   Median :4.333
##  Mean   :5.039   Mean   :4.223
##  3rd Qu.:5.750   3rd Qu.:4.889
##  Max.   :6.000   Max.   :6.000
```

```
newdf <-  data_clean %$%
   expand.grid(S_Subscore  = c(4.75, 5.00, 5.75),
               SP_Subscore = c(3.56, 4.33, 4.89)) %>%
  tibble::rownames_to_column(var = "group")

sp_label <- c("3.56" = "Social Presence Factor: \n Q1 = 3.56", "4.33" =
              "Social Presence Factor: \n Mdn = 4.33",
              "4.89" = "Social Presence Factor: \n Q3 = 4.89")

newdf %>%
  survfit(cox_final_cluster,
          newdata = .) %>%
  broom::tidy() %>%
  tidyr::gather(key = 'key',
                value = 'value',
                -time, -n.risk, -n.event, -n.censor) %>%
  dplyr::mutate(group = substr(key, nchar(key), nchar(key)),
                key   = substr(key, 1, nchar(key) - 2)) %>%
  dplyr::left_join(newdf, 'group') %>%
  tidyr::spread(key, value) %>%
  dplyr::mutate(S_Subscore = factor(S_Subscore) %>% fct_rev) %>%
  ggplot(aes(x     = time,
             y     = estimate,
             group = S_Subscore,
             col   = S_Subscore)) +
  geom_line(aes(linetype = S_Subscore)) +
  facet_grid(. ~ SP_Subscore, labeller = labeller(SP_Subscore =
             sp_label)) +
  theme_bw() +
```

```
theme(legend.key.width = unit(1.5,"cm"),
      legend.background = element_rect(color = "black"),
      legend.position = c(0, 0),
      legend.justification = c(-0.1, -0.1)) +
labs(x = "Time, days",
     y = "Survival Probability") +
scale_color_manual(name="Success Factor\nscale(1-6)",
                   values=c("black","black","black"),
                   labels=c("Q3 = 5.75","Mdn = 5.00",
                            "Q1 = 4.75")) +
scale_linetype_manual(name="Success Factor\nscale(1-6)",
                      values=c("solid","longdash","dotted"),
                      labels=c("Q3 = 5.75","Mdn = 5.00",
                               "Q1 = 4.75"))
```

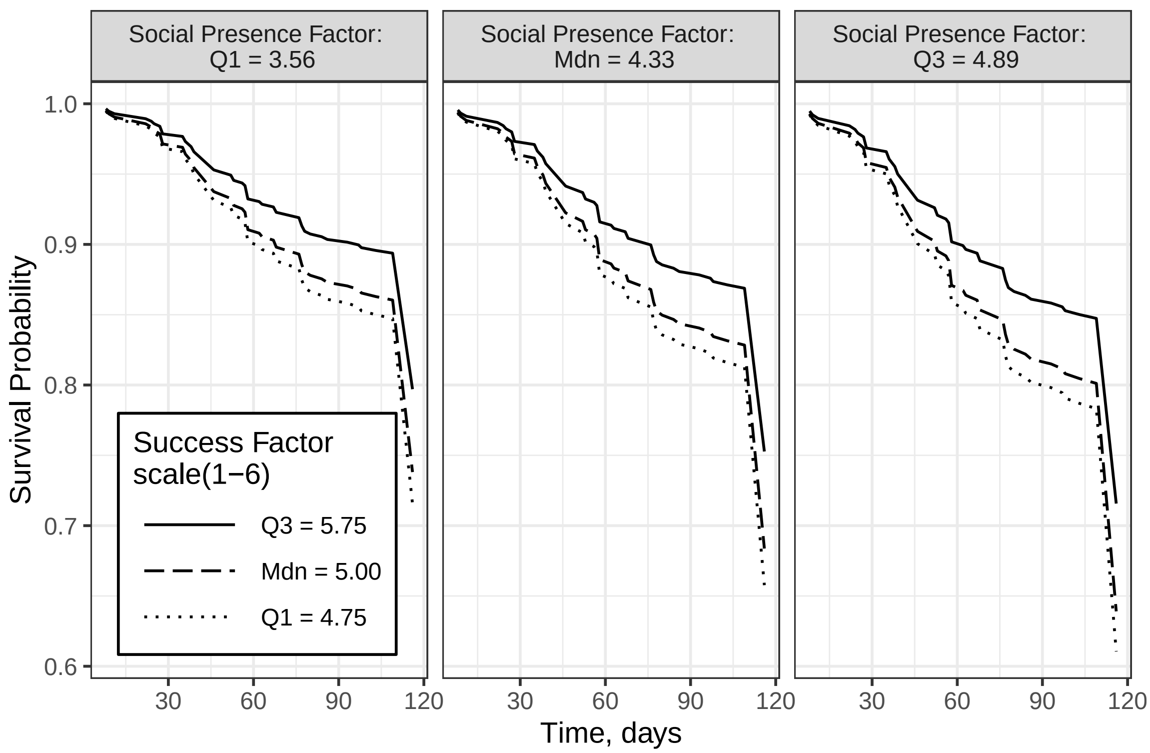

Figure J.18. Visualization of the Final Multilevel Cox Regression Model

Interpretation of Multilevel Cox Regression Model Analysis

Multilevel Cox Regression was a good way to monitor course persistence to time-to-event or survival in a course. The backward stepwise factor removal process reduced the 8-factor model to a 2-factor model with the two factors of 'Success' and 'Social Presence'. The likelihood test showed there was not a significant difference between the 8-factor and 2-factor models.

The researcher also checked the final model with the interaction between the two factors and found no significance and thus determined to not include the interaction in the final model for analysis.

Table J.10 indicated a hazard ratio of 0.700 of the S_Subscore (Success factor), which means that students who scored one point higher on their perception of the Success factor corresponded to a 30% decrease in the log hazard rate. Likewise, students who scored one point higher on their perception of the Social Presence factor corresponded to a 42% increase in the log hazard rate. Figure J.18 shows how this relationship works with an increase of the hazard risk as the students' perception of the Success factor decreases and the student's perception of the Social Presence factor increases.

Multilevel Logistic Regression

Two multilevel logistic regression analyses were performed. First, the researcher performed a multilevel logistic regression analysis measuring the five motivational factors and three learning environment factors to course completion. Second, the researcher performed a multilevel logistic regression analysis comparing the same factors to mathematics retention - measuring if the student enrolled in a mathematics course in Spring 2019 semester.

Completion

The researcher first measured the multilevel logistic regression models for each of the eight independent factors (see Tables J.13 and J.14). Second, the researcher started with the complete 8-factor multilevel logistic regression model and used backward stepwise factor removal approach to get to the final 2-factor model (see Tables J.15, J.16). The interaction between the two factors was also checked to see if there was any significance (see Table J.17).

```
lr_comp_M <- glmer(formula = notCompleted ~ M_Subscore +
     (1 | SchoolID/CourseID), family = "binomial",
     data = data_clean)

lr_comp_U <- glmer(formula = notCompleted ~ U_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_comp_S <- glmer(formula = notCompleted ~ S_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_comp_I <- glmer(formula = notCompleted ~ I_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_comp_C <- glmer(formula = notCompleted ~ C_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_comp_TP <- glmer(formula = notCompleted ~ TP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_comp_SP <- glmer(formula = notCompleted ~ SP_Subscore +
```

```
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_comp_CP <- glmer(formula = notCompleted ~ CP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_comp_all <- glmer(formula = notCompleted ~ M_Subscore + U_Subscore +
    S_Subscore + I_Subscore + C_Subscore + TP_Subscore +
    SP_Subscore + CP_Subscore + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)

lr_comp_7 <- glmer(formula = notCompleted ~ M_Subscore + U_Subscore +
    S_Subscore + I_Subscore + TP_Subscore + SP_Subscore +
    CP_Subscore + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)

lr_comp_6 <- glmer(formula = notCompleted ~ M_Subscore + U_Subscore +
    S_Subscore + I_Subscore + TP_Subscore + SP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial", data = data_clean)

lr_comp_5 <- glmer(formula = notCompleted ~ M_Subscore + U_Subscore +
    S_Subscore + I_Subscore + SP_Subscore + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)

lr_comp_4 <- glmer(formula = notCompleted ~ M_Subscore +
    U_Subscore + S_Subscore + SP_Subscore + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)

lr_comp_3 <- glmer(formula = notCompleted ~ U_Subscore +
    S_Subscore + SP_Subscore + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)

# center S & SP subscores at grand means
lr_comp_final <- glmer(formula = notCompleted ~ I(S_Subscore - 5.039) +
    I(SP_Subscore - 4.233) + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)

# center S & SP subscores at grand means
lr_comp_interaction <- glmer(formula = notCompleted ~ I(S_Subscore -
    5.039)*I(SP_Subscore - 4.233) + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)
```

```
texreg::texreg(list(lr_comp_M, lr_comp_U, lr_comp_S, lr_comp_I),
               custom.model.names = c("M", "U", "S", "I"),
               digits = 3,
               label = "tab:lr_comp_M_U_S_I",
               caption="Multilevel Logistic Regression (Course
               Completion) Models for Independent Factors of
               eMpowerment, Usefulness, Success, and Interest",
               caption.above = TRUE)
```

Table J.13

Multilevel Logistic Regression (Course Completion) Models for Independent Factors of eMpowerment, Usefulness, Success, and Interest

	M	U	S	I
(Intercept)	-0.639	0.091	0.550	-0.076
	(0.666)	(0.591)	(0.717)	(0.608)
M_Subscore	-0.051			
	(0.125)			
U_Subscore		-0.217		
		(0.120)		
S_Subscore			-0.287^{*}	
			(0.136)	
I_Subscore				-0.183
				(0.126)
AIC	409.708	406.654	405.392	407.803
BIC	424.904	421.850	420.588	422.999
Log Likelihood	-200.854	-199.327	-198.696	-199.901
Num. obs.	330	330	330	330
Num. groups: CourseID:SchoolID	36	36	36	36
Num. groups: SchoolID	8	8	8	8
Var: CourseID:SchoolID (Intercept)	0.190	0.158	0.177	0.193
Var: SchoolID (Intercept)	0.178	0.195	0.157	0.151

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

```
texreg::texreg(list(lr_comp_C, lr_comp_TP, lr_comp_SP, lr_comp_CP),
               custom.model.names = c("C", "TP", "SP", "CP"),
               digits = 3,
               label = "tab:lr_comp_C_TP_SP_CP",
               caption="Multilevel Logistic Regression (Course
               Completion) Models for Independent Factors of Care,
               Teaching Presence, Social Presence, and Cognitive
               Presence",
               caption.above = TRUE)
```

Table J.14

Multilevel Logistic Regression (Course Completion) Models for Independent Factors of Care, Teaching Presence, Social Presence, and Cognitive Presence

	C	TP	SP	CP
(Intercept)	-0.613	-1.384	-1.962^{**}	-0.554
	(1.003)	(0.833)	(0.602)	(0.675)
C_Subscore	-0.053			
	(0.183)			
TP_Subscore		0.099		
		(0.161)		
SP_Subscore			0.249^{*}	
			(0.127)	
CP_Subscore				-0.075
				(0.139)
AIC	409.790	409.489	405.895	409.587
BIC	424.987	424.685	421.092	424.784
Log Likelihood	-200.895	-200.745	-198.948	-200.794
Num. obs.	330	330	330	330
Num. groups: CourseID:SchoolID	36	36	36	36
Num. groups: SchoolID	8	8	8	8
Var: CourseID:SchoolID (Intercept)	0.191	0.204	0.217	0.190
Var: SchoolID (Intercept)	0.186	0.192	0.200	0.185

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

```
texreg::texreg(list(lr_comp_all, lr_comp_7, lr_comp_6, lr_comp_5),
               custom.model.names = c("Full", "7", "6", "5"),
               digits = 3,
               label = "tab:lr_comp_all_7_6_5",
               caption="Multilevel Logistic Regression (Course
               Completion) Models for 8, 7, 6, and 5 Factors
               by Removal",
               caption.above = TRUE)
```

Table J.15

Multilevel Logistic Regression (Course Completion) Models for 8, 7, 6, and 5 Factors by Removal

	Full	7	6	5
(Intercept)	-0.273	-0.468	-0.571	-0.200
	(1.083)	(0.932)	(0.919)	(0.811)
M_Subscore	0.276	0.269	0.288	0.311
	(0.210)	(0.209)	(0.209)	(0.207)
U_Subscore	-0.229	-0.230	-0.321	-0.315
	(0.204)	(0.203)	(0.188)	(0.186)
S_Subscore	-0.487^{*}	-0.503^{*}	-0.506^{*}	-0.491^{*}
	(0.225)	(0.221)	(0.221)	(0.219)
I_Subscore	-0.144	-0.153	-0.205	-0.160
	(0.234)	(0.233)	(0.230)	(0.222)
C_Subscore	-0.117			
	(0.331)			
TP_Subscore	0.327	0.256	0.202	
	(0.311)	(0.236)	(0.231)	
SP_Subscore	0.631^{**}	0.631^{**}	0.504^{**}	0.552^{***}
	(0.207)	(0.207)	(0.173)	(0.164)
CP_Subscore	-0.345	-0.327		
	(0.284)	(0.280)		
AIC	400.626	398.749	398.130	396.902
BIC	442.416	436.740	432.322	427.295
Log Likelihood	-189.313	-189.375	-190.065	-190.451
Num. obs.	330	330	330	330
Num. groups: CourseID:SchoolID	36	36	36	36
Num. groups: SchoolID	8	8	8	8
Var: CourseID:SchoolID (Intercept)	0.218	0.221	0.214	0.204
Var: SchoolID (Intercept)	0.229	0.221	0.203	0.200

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

```
texreg::texreg(list(lr_comp_4, lr_comp_3, lr_comp_final),
               custom.model.names = c("4", "3", "Final"),
               digits = 3,
               label = "tab:lr_comp_4_3_final",
               caption="Multilevel Logistic Regression (Course
               Completion) Models for 4, 3, and 2 Factors
               by Removal",
               caption.above = TRUE)

texreg::texreg(list(lr_comp_final, lr_comp_interaction),
               custom.model.names = c("Final", "Interaction"),
               digits = 3,
               label = "tab:lr_comp_final_interaction",
               caption="Multilevel Logistic Regression (Course
               Completion) for Final and Interaction Models",
               caption.above = TRUE)
```

Table J.16

Multilevel Logistic Regression (Course Completion) Models for 4, 3, and 2 Factors by Removal

	4	3	Final
(Intercept)	-0.177	-0.011	-0.928^{***}
	(0.811)	(0.796)	(0.237)
M_Subscore	0.273		
	(0.199)		
U_Subscore	-0.378^{*}	-0.328^{*}	
	(0.165)	(0.160)	
S_Subscore	-0.526^{*}	-0.355^{*}	
	(0.214)	(0.171)	
SP_Subscore	0.532^{***}	0.556^{***}	
	(0.161)	(0.160)	
I(S_Subscore - 5.039)			-0.496^{**}
			(0.157)
I(SP_Subscore - 4.233)			0.442^{**}
			(0.146)
AIC	395.418	395.350	397.516
BIC	422.011	418.145	416.511
Log Likelihood	-190.709	-191.675	-193.758
Num. obs.	330	330	330
Num. groups: CourseID:SchoolID	36	36	36
Num. groups: SchoolID	8	8	8
Var: CourseID:SchoolID (Intercept)	0.185	0.171	0.213
Var: SchoolID (Intercept)	0.221	0.197	0.158

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table J.17

Multilevel Logistic Regression (Course Completion) for Final and Interaction Models

	Final	Interaction
(Intercept)	-0.928^{***}	-0.979^{***}
	(0.237)	(0.241)
I(S_Subscore - 5.039)	-0.496^{**}	-0.425^{*}
	(0.157)	(0.165)
I(SP_Subscore - 4.233)	0.442^{**}	0.460^{**}
	(0.146)	(0.148)
I(S_Subscore - 5.039):I(SP_Subscore - 4.233)		0.126
		(0.097)
AIC	397.516	397.782
BIC	416.511	420.576
Log Likelihood	-193.758	-192.891
Num. obs.	330	330
Num. groups: CourseID:SchoolID	36	36
Num. groups: SchoolID	8	8
Var: CourseID:SchoolID (Intercept)	0.213	0.214
Var: SchoolID (Intercept)	0.158	0.161

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Final Multilevel Logistic Regression (Course Completion) Model Analysis

```
data_clean %>%
  dplyr::filter(complete.cases(S_Subscore, SP_Subscore)) %>%
  furniture::table1(notCompleted)
```

```
##
##
##               Mean/Count (SD/%)
##               n = 330
##  notCompleted
##               0.3 (0.5)
##
```

```
lr_comp_anova <- xtable::xtable(anova(lr_comp_7, lr_comp_final,
                                      test = "Chi"),
               digits = 3,
               label = "tab:Likelihood_lr_comp",
               caption="Comparing Multilevel Logistic Regression
               (Course Completion) Model Fits with Likelihood
               Ratio Test")

print(lr_comp_anova, caption.placement = "top", comment=FALSE)
```

Table J.18

Comparing Multilevel Logistic Regression (Course Completion) Model Fits with Likelihood Ratio Test

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
lr_comp_final	5.000	397.516	416.511	-193.758	387.516			
lr_comp_7	10.000	398.749	436.740	-189.375	378.749	8.767	5.000	0.119

Final Multilevel Logistic Regression (Course Completion) Model Table

```
extract_glmer_exp <- function (model,
                               method = c("naive", "profile",
                                          "boot", "Wald"),
                               level = 0.95,
                               nsim = 1000,
                               include.aic = TRUE,
                               include.bic = TRUE,
                               include.dic = FALSE,
                               include.deviance = FALSE,
                               include.loglik = TRUE,
                               include.nobs = TRUE,
                               include.groups = TRUE,
                               include.variance = TRUE,
                               ...) {
  if (packageVersion("lme4") < 1) {
    message("Please update to a newer 'lme4' version for
            full compatibility.")
  }
  gof <- numeric()
  gof.names <- character()
  gof.decimal <- logical()
  if (include.aic == TRUE) {
    aic <- AIC(model)
    gof <- c(gof, aic)
    gof.names <- c(gof.names, "AIC")
    gof.decimal <- c(gof.decimal, TRUE)
  }
  if (include.bic == TRUE) {
    bic <- BIC(model)
    gof <- c(gof, bic)
    gof.names <- c(gof.names, "BIC")
    gof.decimal <- c(gof.decimal, TRUE)
  }
  if (include.dic == TRUE) {
    is_REML <- lme4::isREML(model)
    llik <- logLik(model, REML = is_REML)
    dev <- deviance(lme4::refitML(model))
    n <- lme4::getME(model, "devcomp")$dims["n"]
    Dhat <- -2 * (llik)
    pD <- dev - Dhat
    DIC <- dev + pD[[1]]
```

```
  gof <- c(gof, DIC)
  gof.names <- c(gof.names, "DIC")
  gof.decimal <- c(gof.decimal, TRUE)
}
if (include.deviance == TRUE) {
  dev <- deviance(lme4::refitML(model))
  gof <- c(gof, dev)
  gof.names <- c(gof.names, "Deviance")
  gof.decimal <- c(gof.decimal, TRUE)
}
if (include.loglik == TRUE) {
  lik <- logLik(model)[1]
  gof <- c(gof, lik)
  gof.names <- c(gof.names, "Log Likelihood")
  gof.decimal <- c(gof.decimal, TRUE)
}
if (include.nobs == TRUE) {
  n <- dim(model.frame(model))[1]
  gof <- c(gof, n)
  gof.names <- c(gof.names, "Num. obs.")
  gof.decimal <- c(gof.decimal, FALSE)
}
if (include.groups == TRUE) {
  grps <- sapply(model@flist, function(x) length(levels(x)))
  grp.names <- names(grps)
  grp.names <- paste("Num. groups:", grp.names)
  gof <- c(gof, grps)
  gof.names <- c(gof.names, grp.names)
  gof.decimal <- c(gof.decimal, rep(FALSE, length(grps)))
}
if (include.variance == TRUE) {
  vc <- as.data.frame(lme4::VarCorr(model))
  for (i in 1:nrow(vc)) {
    if (is.na(vc[i, 2]) && is.na(vc[i, 3])) {
      gof.names <- c(gof.names, "Var: Residual")
    }
    else if (is.na(vc[i, 3])) {
      gof.names <- c(gof.names, paste("Var:", vc[i, 1],
                                      vc[i, 2]))
    }
    else {
      gof.names <- c(gof.names, paste("Cov:", vc[i, 1],
                                      vc[i, 2], vc[i, 3]))
```

```
    }
    gof <- c(gof, vc[i, 4])
    gof.decimal <- c(gof.decimal, TRUE)
  }
}

betas <- lme4::fixef(model, ...)


if ("confint.merMod" %in% methods("confint") && method[1] !=
    "naive") {
  ci <- tryCatch({
    ci <- confint(model, method = method[1], level = level,
                  nsim = nsim, ...)
  }, error = function(err) {
    method <- "naive"
    message(paste("Confidence intervals not available for",
                  "this model. Using naive p values instead."))
  })
  if (is.null(ci)) {
    method <- "naive"
  }
  else {
    last <- nrow(ci)
    number <- length(betas)
    first <- last - number + 1
    ci <- ci[first:last, ]
    if (class(ci) == "matrix") {
      ci.l <- ci[, 1]
      ci.u <- ci[, 2]
    }
    else {
      ci.l <- ci[1]
      ci.u <- ci[2]
    }
  }
}
else if (method[1] != "naive") {
  method[1] <- "naive"
  message(paste("confint.merMod method not found. Using
                naive p values", "instead."))
}
```

```
  if (method[1] == "naive") {
    Vcov <- tryCatch({
      Vcov <- vcov(model, useScale = FALSE, ...)
    }, error = function(err) {
      stop(paste("Please load the Matrix package or update
                 to the latest",
                 "development version of lme4 and run this
                 command again."))
    })
    Vcov <- as.matrix(Vcov)
    se <- sqrt(diag(Vcov))
    zval <- betas/se
    pval <- 2 * pnorm(abs(zval), lower.tail = FALSE)
    tr <- createTexreg(coef.names = names(betas),
                       coef = exp(betas),
                       ci.low = exp(betas - 1.98*se),
                       ci.up  = exp(betas + 1.98*se),
                       pvalues = pval,
                       gof.names = gof.names,
                       gof = gof,
                       gof.decimal = gof.decimal)
  }
  else {
    tr <- createTexreg(coef.names = names(betas),
                       coef   = exp(betas),
                       ci.low = exp(ci.l),
                       ci.up  = exp(ci.u),
                       gof.names = gof.names,
                       gof = gof,
                       gof.decimal = gof.decimal)
  }
  return(tr)
}
```

Function from Sarah Schwartz - retrieved on December 18, 2019: https://github.com/SarBearSchwartz/texreghelpr/blob/master/R/extract_glmer_exp.R

```
texreg::texreg(extract_glmer_exp(lr_comp_final),
               custom.coef.names = c("Reference: S and SP at grand
                                     means",
                                     "S",
                                     "SP"),
```

```
custom.model.names = "OR, Not Completing Course",
caption = "Multilevel Logistic Regression Results",
caption.above = TRUE,
label = "tab:lr_comp_final",
ci.test = 1,
digits = 3,
float.pos = "hb",
single.row = TRUE)
```

Table J.19

Multilevel Logistic Regression Results

	OR, Not Completing Course
Reference: S and SP at grand means	0.396 [0.247; 0.632]*
S	0.609 [0.447; 0.831]*
SP	1.556 [1.165; 2.078]*
AIC	397.516
BIC	416.511
Log Likelihood	-193.758
Num. obs.	330
Num. groups: CourseID:SchoolID	36
Num. groups: SchoolID	8
Var: CourseID:SchoolID (Intercept)	0.213
Var: SchoolID (Intercept)	0.158

* 1 outside the confidence interval

Final Multilevel Logistic Regression (Course Completion) Model Plot

```
effects::Effect(focal.predictors = c("S_Subscore", "SP_Subscore"),
               mod = lr_comp_final,
               xlevels = list(S_Subscore = c(4.75, 5.00, 5.75),
                              SP_Subscore = c(3.56, 4.33, 4.89))) %>%
 data.frame() %>%
  dplyr::mutate(S_Subscore = factor(S_Subscore)) %>%
 ggplot(aes(x = SP_Subscore,
            y = fit)) +
 geom_line(aes(linetype = S_Subscore)) +
 theme_bw() +
  labs(x = "Social Presence Factor (scale 1-6)
  Q1 = 3.56, Mdn = 4.33, Q3 = 4.89",
       y = "Probability of not completing",
       linetype = "Success Factor\n(scale 1-6)") +
  scale_color_manual(values=c("black","black","black"),
                     label=c("Q1 = 4.75","Mdn = 5",
                             "Q3 = 5.75")) +
  scale_linetype_manual(values=c("dotted","longdash","solid"),
                        label=c("Q1 = 4.75","Mdn = 5.00",
                                "Q3 = 5.75"))
```

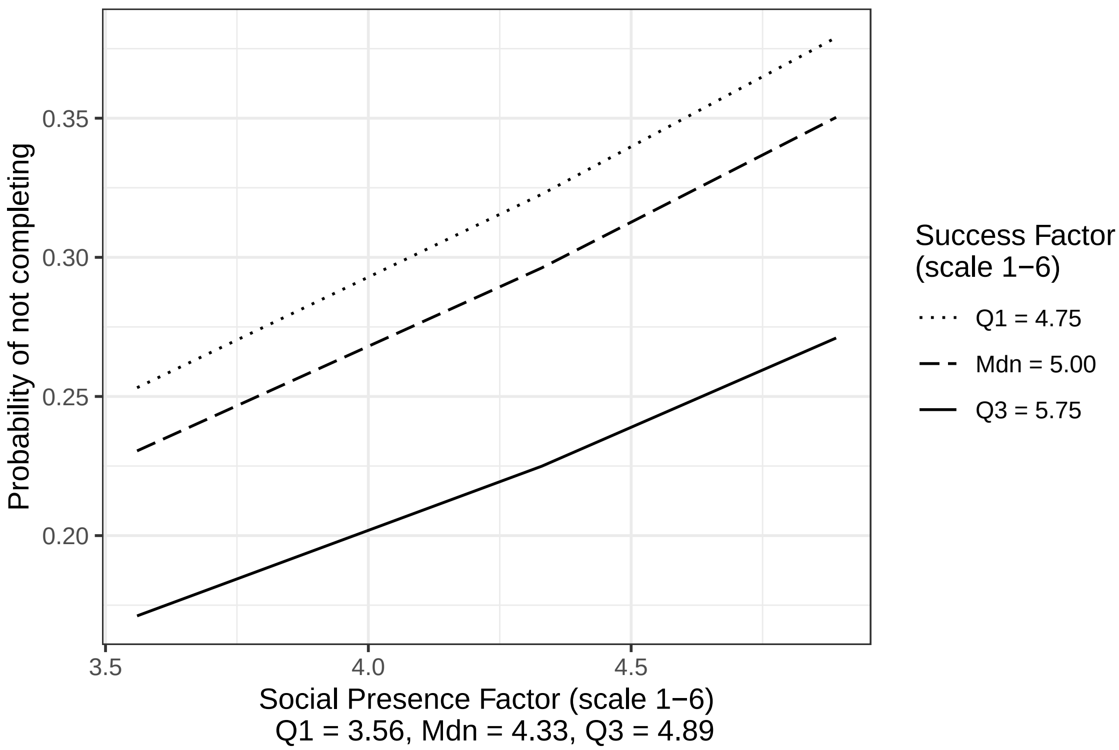

Figure J.19. Final Multilevel Logistic Regression (Course Completion) Model Plot

Interpretation of Multilevel Logistic Regression (Course Completion) Model Analysis

Multilevel Logistic Regression was a good way to monitor course completion and was determined as students who received a 'C-' grade or higher in the class. Similar to the Multilevel Cox Regression Analysis done in the previous section, the backward stepwise factor removal process reduced the 8-factor model to a 2-factor model with the two factors of 'Success' and 'Social Presence'. The likelihood test showed there was not a significant difference between the 8-factor and 2-factor models.

The researcher also checked the final model with the interaction between the two factors and found no significance and thus determined to not include the interaction in the final multilevel logistic regression model for analysis.

Table J.19 indicates a student with the grand means for both S_Subscore (5.039) and SP_Subscore (4.223) has a 40% chance of dropping out. Participants who perceive the Success factor one point higher correspond to a 39% reduction in the odds of dropping out. Participants who perceive the Social Presence factor one point higher correspond to a 56% increase in the odds of dropping out. Figure J.19 demonstrates the visualization of this multilevel logistic regression by showing how this relationship works with an increase of the probability of dropping out as the students' perception of the Success Factor decreases and the student's perception of the Social Presence Factor increases.

Retention

The researcher first measured the multilevel logistic regression models for each of the eight independent factors (see Tables J.20 and J.21). Second, the researcher started with the complete 8-factor multilevel logistic regression model and used backward stepwise factor removal approach to determine the most significant model (see Tables J.22 and J.23).

```
lr_ret_M <- glmer(formula = EnrolledSpring2019 ~ M_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_U <- glmer(formula = EnrolledSpring2019 ~ U_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_S <- glmer(formula = EnrolledSpring2019 ~ S_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_I <- glmer(formula = EnrolledSpring2019 ~ I_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_C <- glmer(formula = EnrolledSpring2019 ~ C_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_TP <- glmer(formula = EnrolledSpring2019 ~ TP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_SP <- glmer(formula = EnrolledSpring2019 ~ SP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_CP <- glmer(formula = EnrolledSpring2019 ~ CP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_all <- glmer(formula = EnrolledSpring2019 ~ M_Subscore +
    U_Subscore + S_Subscore + I_Subscore + C_Subscore + TP_Subscore +
    SP_Subscore + CP_Subscore + (1 | SchoolID/CourseID),
```

```
    family = "binomial", data = data_clean)

lr_ret_7 <- glmer(formula = EnrolledSpring2019 ~ M_Subscore +
    U_Subscore + S_Subscore + I_Subscore + C_Subscore + TP_Subscore +
    SP_Subscore + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)

lr_ret_6 <- glmer(formula = EnrolledSpring2019 ~ M_Subscore +
    U_Subscore + S_Subscore + I_Subscore + C_Subscore + SP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial", data = data_clean)

lr_ret_5 <- glmer(formula = EnrolledSpring2019 ~ M_Subscore +
    U_Subscore + I_Subscore + C_Subscore + SP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial", data = data_clean)

lr_ret_4 <- glmer(formula = EnrolledSpring2019 ~ M_Subscore +
    I_Subscore + C_Subscore + SP_Subscore +
    (1 | SchoolID/CourseID), family = "binomial",
    data = data_clean)

lr_ret_3 <- glmer(formula = EnrolledSpring2019 ~ M_Subscore +
    I_Subscore + SP_Subscore + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)

lr_ret_final <- glmer(formula = EnrolledSpring2019 ~ I_Subscore +
    SP_Subscore + (1 | SchoolID/CourseID),
    family = "binomial", data = data_clean)
```

```
texreg::texreg(list(lr_ret_M, lr_ret_U, lr_ret_S, lr_ret_I),
               custom.model.names = c("M", "U", "S", "I"),
               digits = 3,
               label = "tab:lr_ret_M_U_S_I",
               caption="Multilevel Logistic Regression (Retention)
               Models for Independent Factors of eMpowerment,
               Usefulness, Success, and Interest",
               caption.above = TRUE)
```

Table J.20

Multilevel Logistic Regression (Retention) Models for Independent Factors of eMpowerment, Usefulness, Success, and Interest

	M	U	S	I
(Intercept)	0.325	0.575	0.577	0.253
	(0.671)	(0.606)	(0.728)	(0.620)
M_Subscore	0.133			
	(0.119)			
U_Subscore		0.090		
		(0.113)		
S_Subscore			0.081	
			(0.130)	
I_Subscore				0.165
				(0.120)
AIC	426.738	427.353	427.598	426.106
BIC	441.934	442.549	442.794	441.302
Log Likelihood	-209.369	-209.676	-209.799	-209.053
Num. obs.	330	330	330	330
Num. groups: CourseID:SchoolID	36	36	36	36
Num. groups: SchoolID	8	8	8	8
Var: CourseID:SchoolID (Intercept)	0.000	0.000	0.000	0.000
Var: SchoolID (Intercept)	0.526	0.547	0.538	0.534

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

```
texreg::texreg(list(lr_ret_C, lr_ret_TP, lr_ret_SP, lr_ret_CP),
               custom.model.names = c("C", "TP", "SP", "CP"),
               digits = 3,
               label = "tab:lr_ret_C_TP_SP_CP",
               caption="Multilevel Logistic Regression (Retention)
               Models for Independent Factors of Care, Teaching
               Presence, Social Presence, and Cognitive Presence",
               caption.above = TRUE)
```

Table J.21

Multilevel Logistic Regression (Retention) Models for Independent Factors of Care, Teaching Presence, Social Presence, and Cognitive Presence

	C	TP	SP	CP
(Intercept)	0.871	0.637	1.436*	0.903
	(0.989)	(0.802)	(0.590)	(0.677)
C_Subscore	0.022			
	(0.176)			
TP_Subscore		0.072		
		(0.151)		
SP_Subscore			−0.106	
			(0.115)	
CP_Subscore				0.018
				(0.131)
AIC	427.972	427.763	427.146	427.968
BIC	443.169	442.959	442.342	443.164
Log Likelihood	-209.986	-209.882	-209.573	-209.984
Num. obs.	330	330	330	330
Num. groups: CourseID:SchoolID	36	36	36	36
Num. groups: SchoolID	8	8	8	8
Var: CourseID:SchoolID (Intercept)	0.000	0.000	0.000	0.000
Var: SchoolID (Intercept)	0.540	0.543	0.547	0.539

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

```
texreg::texreg(list(lr_ret_all, lr_ret_7, lr_ret_6, lr_ret_5),
               custom.model.names = c("Full", "7", "6", "5"),
               digits = 3,
               label = "tab:lr_ret_all_7_6_5",
               caption="Multilevel Logistic Regression (Retention)
               Models for 8, 7, 6, and 5 Factors by Removal",
               caption.above = TRUE)
```

Table J.22

Multilevel Logistic Regression (Retention) Models for 8, 7, 6, and 5 Factors by Removal

	Full	7	6	5
(Intercept)	1.117	1.087	1.071	1.036
	(1.043)	(1.031)	(1.028)	(1.021)
M_Subscore	0.129	0.131	0.141	0.117
	(0.190)	(0.190)	(0.189)	(0.172)
U_Subscore	0.017	0.005	0.008	0.003
	(0.186)	(0.171)	(0.171)	(0.171)
S_Subscore	−0.048	−0.050	−0.062	
	(0.205)	(0.204)	(0.203)	
I_Subscore	0.280	0.272	0.292	0.282
	(0.218)	(0.213)	(0.212)	(0.209)
C_Subscore	−0.280	−0.272	−0.137	−0.155
	(0.307)	(0.304)	(0.236)	(0.229)
TP_Subscore	0.205	0.192		
	(0.281)	(0.271)		
SP_Subscore	−0.271	−0.287	−0.252	−0.252
	(0.174)	(0.150)	(0.142)	(0.142)
CP_Subscore	−0.045			
	(0.259)			
AIC	435.237	433.268	431.765	429.856
BIC	477.027	471.259	465.957	460.249
Log Likelihood	-206.619	-206.634	-206.882	-206.928
Num. obs.	330	330	330	330
Num. groups: CourseID:SchoolID	36	36	36	36
Num. groups: SchoolID	8	8	8	8
Var: CourseID:SchoolID (Intercept)	0.000	0.000	0.000	0.000
Var: SchoolID (Intercept)	0.550	0.549	0.535	0.537

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

```
texreg::texreg(list(lr_ret_4, lr_ret_3, lr_ret_final),
               custom.model.names = c("4", "3", "Final"),
               digits = 3,
               label = "tab:lr_ret_4_3_final",
               caption="Multilevel Logistic Regression (Retention)
               Models for 4, 3, and 2 Factors by Removal",
               caption.above = TRUE)
```

Table J.23

Multilevel Logistic Regression (Retention) Models for 4, 3, and 2 Factors by Removal

	4	3	Final
(Intercept)	1.038	0.568	0.719
	(1.014)	(0.733)	(0.675)
M_Subscore	0.118	0.087	
	(0.170)	(0.164)	
I_Subscore	0.283	0.250	0.302^{*}
	(0.182)	(0.175)	(0.144)
C_Subscore	−0.155		
	(0.229)		
SP_Subscore	−0.252	−0.264	−0.253
	(0.140)	(0.139)	(0.137)
AIC	427.856	426.316	424.598
BIC	454.450	449.111	443.593
Log Likelihood	-206.928	-207.158	-207.299
Num. obs.	330	330	330
Num. groups: CourseID:SchoolID	36	36	36
Num. groups: SchoolID	8	8	8
Var: CourseID:SchoolID (Intercept)	0.000	0.000	0.000
Var: SchoolID (Intercept)	0.537	0.539	0.547

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Final Multilevel Logistic Regression (Retention) Model Analysis

```
data_clean %>%
  dplyr::filter(complete.cases(I_Subscore, SP_Subscore)) %>%
  furniture::table1(EnrolledSpring2019)
```

```
##
##
##                       Mean/Count (SD/%)
##                       n = 330
##  EnrolledSpring2019
##     N                 129 (39.1%)
##     Y                 201 (60.9%)
##
```

```r
lr_ret_anova <- xtable::xtable(anova(lr_ret_all, lr_ret_final,
                                      test = "Chi"),
               digits = 3,
               label = "tab:Likelihood_lr_ret",
               caption="Comparing Multilevel Logistic Regression
               (Retention) Model Fits with Likelihood Ratio Test")

print(lr_ret_anova, caption.placement = "top")
```

% latex table generated in R 3.6.1 by xtable 1.8-4 package % Wed Feb 26 18:53:38 2020

Table J.24

Comparing Multilevel Logistic Regression (Retention) Model Fits with Likelihood Ratio Test

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
lr_ret_final	5.000	424.598	443.593	-207.299	414.598			
lr_ret_all	11.000	435.237	477.027	-206.619	413.237	1.361	6.000	0.968

Interpretation of Multilevel Logistic Regression (Retention) Model Analysis

The clustering factor of courses model did not converge, so the researcher only clustered by schools. Analysis of the multilevel logistic regression models did not demonstrate any significant factors on student retention for enrolling in the subsequent semester. The Interest Factor did show some significance in the 2-factor model. However, it was not significant in the single-factor model of Interest.

CURRICULUM VITAE

Samuel K. Gedeborg

Address: College of Education and Human Services
2805 Old Main Hill
Logan, Utah 84321
Email: sgedeborg@gmail.com

EDUCATION

Ph.D. Curriculum and Instruction | *Expected: Mar 2020*
Mathematics Education and Leadership
Utah State University, Logan, UT

How Student Perceptions of the Online Learning Environment and Student Motivation Predict Persistence, Completion, and Retention in Developmental Mathematics Courses

Master of Educational Technology | *May 2011*
Boise State University, Boise, ID
Graduate Certificate: School Technology Coordination

B.S. Mathematics, Secondary Education | *May 2006*
Boise State University, Boise, ID
Minors: Computer Science, Spanish

LICENSES AND CERTIFICATIONS

Qualtrics Research Core Expert Certification Mar 2018
Qualtrics Research Core Software

Certified Member of Association for Learning Technology Nov 2017
Association for Learning Technology (ALT), Oxfordshire, UK

Graduate Certificate in School Technology Coordination May 2011
Boise State University, Boise, ID

Idaho Secondary Education 6/12: Math, Spanish, Technology 2006-current
Idaho State Department of Education, Boise, ID

EMPLOYMENT HISTORY

UTAH VALLEY UNIVERSITY

OTL Lab Director, Office of Teaching and Learning 2019-current

Utah Valley University (Orem, UT): *Responsibilities include leading team in the Office of Teaching and Learning technology lab with a vision to improve student learning outcomes and facilitate technology-infused teaching through training and support of UVU faculty.*

Instructional Designer II, Office of Teaching and Learning 2012-2019

Utah Valley University (Orem, UT): *Responsibilities included assisting faculty in the development of course work, particularly with hybrid and online courses. Provided support for Learning Management System (LMS), course design, need assessment and curriculum. In this position, provided faculty training, design and development support that encourages innovative use of technology in learning and teaching.*

Adjunct Instructor, Developmental Mathematics 2013-2014

Utah Valley University (Orem, UT): *Responsibilities included teaching assigned courses in Developmental Mathematics from the Department through preparing course instruction materials and assessing student understanding of learning objectives.*

BRIGHAM YOUNG UNIVERSITY-IDAHO

Online Adjunct Instructor, PathwayConnect 2014-current
Instructor Development Lead 2019–current
Online Course Representative, MATPC 100L 2019-current
Teaching Group Leader 2014–2015, 2017–2019

Brigham Young University-Idaho (Rexburg, ID): *Responsibilities as an Online Instructor include teaching coursework as assigned by the University, foster student understanding, monitor progress, and offer support to complete online coursework. As an Instructor Development Lead, provide leadership and mentorship to 8 Teaching Group Leaders as assigned by Brigham Young University-Idaho. As Online Course Representative, facilitate community conversations on course specific best online teaching practices, manage accepted answers to questions about course issues, reorganize topics to promote instructor collaboration. As a Teaching Group Leader, provided faculty support, guidance, direction, professional development, and supervision to 7-10 Online Instructors as assigned by Brigham Young University-Idaho.*

PUBLIC SCHOOL TEACHING EXPERIENCE – 6 YEARS

High School Teacher, Mathematics, Computers, Spanish 2008-2012

Victory Charter School (Nampa, ID): *Taught coursework in Algebra 2, Geometry, Algebra 1, Computer Networking, Computer Programming, Web Design, Multimedia, Spanish 1, Spanish 2. Served as Junior Class Adviser and Assistant Technology Coordinator. Head Coach for Academic Decathlon, Math and Science Quiz Bowl, Track, and Cross Country teams.*

Middle School Teacher, Grades 7/8 Mathematics 2007-2008

West Middle School, Nampa School District (Nampa, ID): *Taught coursework in Algebra 1, Pre-algebra, and Basic Mathematical Concepts.*

High School Teacher, Mathematics 2006-2007

Timberline High School / Borah High School, Boise School District (Boise, ID): *Taught coursework in Pre-Calculus, Geometry, Algebra 2, and Pre-algebra.*

RESEARCH

Research Interests:

- Predictive models of course completion and retention. Factors of student success, motivation, and learning environment in varying delivery modalities.
- Mathematical learning and development of non-traditional students.
- Faculty and pre-service professional development, particularly in Technological Pedagogical and Content Knowledge (TPACK) approaches.
- Curriculum design – best practices with using technology in online and blended modalities, mobile learning, problem-based learning, motivation and game-based learning.

PUBLICATIONS

Journal Articles (Refereed)

Nadelson, L. S., Juth, S. M., Hartman, C., **Gedeborg, S.**, & Glaze, A. (2018). Pioneers in unknown territory: Teacher perceptions and use of non-conventional instructional tools. *International Journal of Educational Technology and Learning, 3*(1), 1-16.

Gedeborg, S. (2016). Designing social online math activities. *Mathematics Teacher, 110*(4), 272-278.

Gedeborg, S. (2015). Value of personalized flipped instruction. *Utah Mathematics Teacher Fall/Winter 2015-2016, 8*, 77-80.

Book Chapters (Refereed)

Gedeborg, S., & Bye, C. M. (2018). Social interactions in an online environment: Developing mathematical process standards. *Education Research Highlights in Mathematics, Science and Technology 2018*, 56-65.

PRESENTATIONS

Invited Presentations

Gedeborg, S. (2019, October). Lightning Talk: Online student success and retention. *Fall Forum – BYU-I*, Rexburg, ID. **(virtual presentation)** *Invited to give a modified version of presentation offered at Online Learning & Teaching Conference (2019, June)*

Gedeborg, S. (2019, June). Lightning Talk: Open their eyes. *Online Learning & Teaching Conference – BYU-I*, Rexburg, ID.

Gedeborg, S. (2017, October). Improved student learning behaviors through gamified course design. *Utah Instructional Design Summit*, Orem, UT.

Alden-Rivers, B., **Gedeborg, S.**, & Huyett, S.(2017, April). Gateway vs gatekeeper courses: Course redesign project. *USHE College Access & Completion Retreat*, Salt Lake City, UT.

Gedeborg, S. (2015, February). Implementing gamification into a blended course design. *PASSHE Virtual Conference,* Harrisburg, PA. **(virtual presentation)** *Invited to give a modified version of presentation offered at OLC Blended Conference (2014, July)*

National Presentations

Gurell, S., & **Gedeborg, S.** (2019, November). Building the freeway to the future: A case study in online course quality review. *OLC Accelerate 2019*, Orlando, FL.

Gedeborg, S., & Sellers, L.(2018, November). Gateway getaway: Course redesign initiative at Utah Valley University. *14th Annual National Symposium on Student Retention*, Salt Lake City, UT. **(poster presentation)**

Gedeborg, S. (2017, March). Increasing student active learning with Qualtrics. *1st Annual Teaching for Learning Conference*, Orem, UT.

Gedeborg, S. (2014, July). Implementing gamification into a blended course design. *Online Learning Consortium Blended Learning Conference & Workshop*, Denver, CO.

Gedeborg, S. (2013, July). Institutional blended standards: Develop to improve development. *10th Annual Sloan Consortium Blended Learning Conference & Workshop*, Milwaukee, WI.

State and Regional Presentations

Gurell, S.,& **Gedeborg, S.** (2018, October). Beyond drill and practice: Ideas to enhance students' online learning experience. *Southwest Association for Developmental Education*, Orem, UT.

Gedeborg, S. (2016, November). Improving student engagement by building math activities with web-based software tools. *2016 Utah Council of Teachers of Mathematics Conference*, Salt Lake City, UT.

Gedeborg, S., Hill, J., & Olsen, J. (2016, April). Student knowledge of hybrid courses during scheduling. *8th Annual Scholarship of Teaching and Engagement Conference*, Orem, UT.

Gedeborg, S. (2015, November). Personalizing flipped instruction. *2015 Utah Council of Teachers of Mathematics Conference*, Lehi, UT.

Gurell, S., & **Gedeborg, S.** (2015, March). What is really going on here?: Discussing Kaltura analytics with faculty. *Spring 2015 ID Summit*, Salt Lake City, UT.

Gurell, S., **Gedeborg, S.**, & Delgadillo, D. (2014, March). Implications of sharing undergraduate research. *2014 Scholarship of Teaching & Engagement Conference*, Orem, UT.

Local Presentations

Brinkerhoff, R., & **Gedeborg, S.** (2019, October). Faculty development: Creating an online course to promote student success *UC Conference on Student Success*, Orem, UT.

Gedeborg, S., Hill, J. (2019, August). Working Smarter with Canvas. *2019 Faculty Convocation*, Orem, UT.

Gedeborg, S. (2019, June). Online student success and retention: Selling more than just learning. *Online Learning & Teaching Conference – BYU-I*, Rexburg, ID.

Gedeborg, S., & Caka, F. (2019, February). Designing interactive activities with Qualtrics. *UVU Technology Conference*, Orem, UT.

Gedeborg, S. (2018, June). Instructor online presence and communication: Bridging cultural differences. *Online Learning & Teaching Conference – BYU-I*, Rexburg, ID.

Gedeborg, S., Nixon, J. (2016, October). Adding badges to your Canvas course. *2nd Annual Fall Ideas Fair: Games to Engage Learners*, Orem, UT. **(poster presentation)**

Gedeborg, S. (2015, October). Educational design using game theory. *Fall Ideas Fair: Games to Engage Learners*, Orem, UT. **(poster presentation)**

Gedeborg, S. (2015, June). Creating a stressful online environment. *Online Learning & Teaching Conference – BYU-I*, Rexburg, ID. **(virtual presentation)**

Gedeborg, S. , Delgadillo, D. (2015, May). Build a personalized financial planner in Excel. *2015 UVU Summer University*, Orem, UT.

Gedeborg, S. (2015, February). Using TurnItIn features and LTI integration in Canvas. *2015 Concurrent Enrollment Conference*, Orem, UT.

Gedeborg, S. (2014, September). Game-based learning: Discovering engagement through gaming. *2014 Wolverine Technology Showcase*, Orem, UT.

Toleman, A., Gurell, S., Morris, T., Sorenson, U., & **Gedeborg, S.** (2014, August). Technology and inclusion. *2014 Utah Valley University Convocation*, Orem, UT.

Gedeborg, S. (2014, June). Understanding hybrid instruction from a professor and a student perspective. *2014 Annual UVU Advisement Conference*, Heber City, UT.

Gurell, S., **Gedeborg, S.**, & Delgadillo, D. (2013, May). Web applications to help with personal productivity, finances, and fitness. *2013 UVU Summer University*, Orem, UT.

TEACHING

Brigham Young University-Idaho, Rexburg, Idaho (2014-current)

PC-102L – Professional Skills (online)
Undergraduate Course. Students strengthen career skills, learn decision making strategies, practice professional communication, and collaborate with others to solve problems.

MATH-100L/G – Intro to Algebra and Finance (online)
Undergraduate Course. Students recap, learn, and retain the fundamentals of basic mathematics and algebra. Students will gain competency in entry-level college math skills; use Excel spreadsheet software to perform mathematical and financial computations; apply math skills to financial decisions such as loan payments, savings, and budgeting; and discuss provident living topics (e.g., self-reliance, stewardship, and personal finance). English language development is also emphasized as math and everyday vocabulary, as well as mechanics and grammar, are applied in speaking, listening, reading, and writing.

FDMAT-108 – Mathematical Tools for the Real World (online)
Undergraduate Course. A course designed to meet the mathematical needs of the liberal arts student. Topics may include mathematical modeling, regression, finance mathematics, probability, statistics, logic, and mathematical patterns and aesthetics.

Utah Valley University, Orem, Utah (2013-2014)

MAT-0990 – Introductory Algebra (face-to-face)
Undergraduate Course. Teaches integers, solving equations, polynomial operations, factoring polynomials, systems of equations and graphs, rational expressions, roots, radicals, complex numbers, quadratic equations and the quadratic formula.

MAT-1010 – Intermediate Algebra (face-to-face)
Undergraduate Course. Expands and covers in more depth basic algebra concepts introduced in Beginning Algebra. Topics of study include linear and quadratic equations and inequalities, polynomials and rational expressions, radical and exponential expressions and equations, complex numbers, systems of linear and nonlinear equations, functions, conic sections, and real-world applications of algebra.

PROFESSIONAL SERVICE

National

Reviewer:

Journal Reviewer: NCTM 2017-current
Mathematics Teacher: Learning and Teaching Pre-K–12

Journal Reviewer: NCTM 2014-2017
Mathematics Teacher

Institutional - Utah Valley University

Champion Roles:

Hybrid Course Design, Co-Champion Apr 2015-current
Duties included taking the lead with Hybrid initiatives at UVU, such as the New Normal project. Engaged in national training and networking activities and remained up-to-date with current literature to ensure we are operating with best practices in mind. Worked with scheduling and other issues, questions, concerns and developments with hybrid courses.

Gateway Course Design, Co-Champion Apr 2015-current
Duties included leading the redesign activities for the Gateway Course Initiative. This was a three-year project to redesign large courses using the NCAT methodology. Engaged in NCAT training and used expertise to train others at the university.

Committees:

UVU Faculty Technology Conference, Co-Chair February 7, 2020
Organized conference agenda, invited and created list of presentors and workshops.

Instructional Designer I Search Committee, Member Sep 2018–Oct 2018
Duties included, ranking of potential candidates and on campus interviews.

Videographer Search Committee, Member Jun 2018–Jul 2018
Duties included, ranking of potential candidates, phone/Skype interviews, and on campus visits.

Instructional Designer II Search Committee, Chair Jan 2018–Mar 2018

Duties included organizing committee meetings, ranking of potential candidates, setting up and conducting phone/Skype interviews, and preparing for candidate visits.

Instructional Designer II Search Committee, Chair Sep 2017–Oct 2017
Duties included organizing committee meetings, ranking of potential candidates, setting up and conducting phone/Skype interviews, and preparing for candidate visits.

Graphic Designer Search Committee, Member Aug 2017–Sep 2017
Duties included, ranking of potential candidates, phone/Skype interviews, and on campus visits.

Sr. Director, OTL Search Committee, Member Mar 2017–Jul 2017
Duties included, ranking of potential candidates, phone/Skype interviews, and on campus visits.

Instructional Designer II Search Committee, Chair Dec 2015–Mar 2016
Duties included organizing committee meetings, ranking of potential candidates, setting up and conducting phone/Skype interviews, and preparing for candidate visits.

SoTE/HETL Conference Committee, Member Apr 2014–Feb 2015
Some duties included planning the conference, activities and room assignments, served as a moderator and timekeeper at sessions, helped with registration and sign-ups.

Instructional Designer II Search, Member Nov 2014–Jul 2015
Duties included, ranking of potential candidates, phone/Skype interviews, and on campus visits. Due to reorganization purposes this job search was suspended and then completed later in 2015.

Workshops and Trainings:

Engaged Learning in Any Environment, Facilitator 2016-2017
"With the popularity of e-learning, it occurred to me that the e should mean more than electronic. If we are going to call it e-learning, shouldn't it be effective, efficient, and engaging" ~ M David Merrill ~ This 2-hour workshop will discuss the principles behind engaged learning (Community of Inquiry and Active Learning), discuss strategies and ideas to engage learners and ways to implement and evaluate progress.

Gateway Getaway, Facilitator 2016-2017
This three-part workshop series helps faculty through redesigning high enrollment courses that have low completion rates at Utah Valley University. The workshops

use the 6 models of instruction and 8 essential elements developed by the National Center for Academic Transformation along with Backwards Design strategies to improve completions rates and lower cost.

Flexible Course Design Studio, Facilitator 2016-2017
This three-part workshop series helps instructors understand the underlying principles, research and ideas of designing an online or hybrid course before development. The first workshop focuses on course vision, learning outcomes and blueprinting. The second workshop focuses on assessment, social learning and E-tivities. The third workshop focuses upon an evaluation of where the design process is and next steps towards development of the course.

Measuring Outcomes and Rubrics in Canvas, Facilitator 2015
Whether one's focus is on competency-based learning or improving the ability of measuring certain levels of performance and student deficiencies, Canvas offers tools that help with measuring student outcomes and making it easier for instructors to assess. Come discover how to maximize the value of these tools.

Project-Based Learning in Mathematics Course, Facilitator 2015
Project-based learning offers an approach to learning through the scope and depth of the activities to build upon previous knowledge and offer opportunities for transfer and utilization. In a real-life environment, there are no clear solutions or answers available in the back of the book. Working in a project-based environment (and particularly a social one) can provide skills, confidence and strategies that students need to succeed outside the academic environment. This workshop will discuss some best practices and strategies to apply in adding an element of project-based learning into the class.

Game-Based Learning Theory and Design, Facilitator 2013-2015
Video games create a $65 billion industry. Still, games in the classroom have had a mixed history in the classroom. This workshop will look at the recent calls for the "gamification" of the classroom and how to implement techniques into an academic environment.

Gradebook Strategies, Facilitator 2013-2015
Technology has increased the ability for instructors to give quick and concise feedback to our students. More than that, it can streamline the grading process to save time, effort and energy so that the focus of grading is upon offering qualitative, formative feedback to students to improve the quality of work.

Qualtrics Tool Use for Research/Teaching, Facilitator 2014
Qualtrics is arguably one of the best professional survey instruments that is currently on the market and learning how to improve teaching and research through using this tool is a valuable skill that will help collect useful data to improve the quality of teaching and contributing to research.

Digital Badges and Competency-Based Learning, Facilitator 2014-2015
Badges in education is a growing trend thanks to technology which makes it easier to develop, award, and share these digital credentials. Being tied to competency-based learning, badges are given to a student to acknowledge they have learned a skill, trade, or achievement. This workshop discusses the basics of badges, how to develop them, and share strategies of implementing them into your course.

TurnItIn: Checking Student Work through Originality Software, Facilitator 2014-2015
TurnItIn is a tool to help assess the originality of documents and much more. Find out what TurnItIn can do for your class and how to maximize the value it can offer to improve grading.

Adaptive Learning Environments and Educational Learning, Facilitator 2013-2014
Technology improvements have helped with the ability to create unique learning environments and to change experiences for students to fit individualized needs. The workshop will also discuss best practices in adapting learning and how to apply adaptive principles into a course.

Develop S.M.A.R.T. Learning Outcomes from Teaching Taxonomies, Facilitator 2013-2014
Writing learning outcomes that align and match course objectives, department goals and the university mission are important to help with assessment, activities, and ultimately learning. This workshop will help with looking at commonly accepted taxonomies and how to develop outcomes that align with desired processes.

Hybrid Learning Activities: The Recipe Model, Facilitator 2013-2014
The variety in which we create assignments and help support learning is about as diverse as the different cuisine one can try. Learning how to adapt, change and fit an activity to match a desired outcome is a valuable skill for any class, especially when deciding whether the activity should be online or face-to-face.

Evaluating Web 2.0 Tools: Purpose, Relevance, and Sustainability, Facilitator 2012
Internet software and online tools create a broad and diverse area which can be tricky to navigate. Finding educational tools that will help with instruction and knowing how to evaluate such tools is an important skill for the 21st Century.

Faculty Reading Learning Circles:.

Small Teaching Online, Facilitator 2019-2020
The concept of small teaching is simple: small and strategic changes have enormous power to improve student learning. Instructors face unique and specific

challenges when teaching an online course. This book offers small teaching strategies that will positively impact the online classroom.

Evidence-Based Online Teaching Best Practices, Facilitator 2019
This learning circle focuses on empirical evidence-based strategies and research in online teaching and learning. Weekly discussions will be shaped from reading current literature in online best practices. These discussions will center around questions and challenges with online courses and how we can improve student success and quality instruction.

Discussion-Based Online Teaching To Enhance Student Learning: Theory, Practice, and Assessment, Facilitator 2018
This book offers an engaging and practical approach to online teaching that is rooted in the author's experience and enthusiasm for creating a virtual environment that engages students and fosters their deep learning. This is a book for all educators and administrators in higher education, in any discipline, engaged in, or contemplating offering, online classes that involve discussion or collaborative learning. It is relevant both to faculty teaching a hybrid and face-to-face classes, and courses conducted entirely online.

Brain Rules (Updated and Expanded): 12 Principles for Surviving and Thriving at Work, Home, and School, Facilitator 2018
Most of us have no idea what's really going on inside our heads. Yet brain scientists have uncovered details every business leader, parent, and teacher should know—like the need for physical activity to get your brain working its best. In Brain Rules, Dr. John Medina, a molecular biologist, shares his lifelong interest in how the brain sciences might influence the way we teach our children and the way we work.

Facilitating Seven Ways of Learning: A Resource for More Purposeful, Effective, and Enjoyable College Teaching, Facilitator 2017
Research on learning clearly demonstrates that learning is not one thing, but many. The learning associated with developing a skill is different from the learning associated with understanding and remembering information, which in turn is different from thinking critically and creatively, solving problems, making decisions, or change paradigms in the light of evidence. Differing outcomes involve different ways of learning and teaching strategies.

The Blended Course Design Workbook: A Practical Guide, Facilitator 2017
Blended (also called hybrid) classrooms, in which face-to-face interaction is intentionally combined with online activities to aid student learning, are becoming more and more common. The blended model is proving to be an environment that provides more self-directed, technology-mediated learning experiences for students

who will be incorporating technology more and more into their professional lives post-college.

Gamify Your Classroom: A Field Guide to Game-Based Learning, Facilitator 2017

This book is a field guide on how to implement game-based learning and «gamification» techniques to the everyday teaching. It is a survey of best practices aggregated from interviews with experts in the field. Each chapter concludes with practical lesson plan ideas, games to play (both digital and tabletop), and links to research further. Much of the book draws on the author's experiences implementing games with his middle school students. Regardless of your teaching discipline or grade level, whether you are a pre-service teacher or veteran educator, this book will engage and reinvigorate the way you teach and how your students learn!

Teaching Online (Tech.edu: A Hopkins Series on Education and Technology), Facilitator 2016

Teaching Online presents instructors with a thoughtful synthesis of educational theory, research, and practice as well as a review of strategies for managing the instructional changes involved in teaching online. In addition, this book presents examples of best practices from successful online instructors as well as cutting-edge ideas from leading scholars and educational technologists. Faculty members, researchers, instructional designers, students, administrators, and policy makers who engage with online learning will find this book an invaluable resource.

The Online Teaching Survival Guide: Simple and Practical Pedagogical Tips, Facilitator 2016

The Online Teaching Survival Guide offers faculty a wide array of theory-based techniques designed for online teaching and technology-enhanced courses. Written by two pioneers in distance education, this guidebook presents practical instructional strategies spread out over a four-phase timeline that covers the lifespan of a course. The book includes information on a range of topics such as course management, social presence, community building, and assessment. Based on traditional pedagogical theory, The Online Teaching Survival Guide integrates the latest research in cognitive processing and learning outcomes. Faculty with little knowledge of educational theory and those well versed in pedagogy will find this resource essential for developing their online teaching skills.

How to Design and Teach a Hybrid Course: Achieving Student-Centered Learning through Blended Classroom, Online and Experiential Activities, Facilitator 2014-2015

Jay Caulfield defines hybrid courses as ones where not only is face time replaced to varying degrees by online learning, but also by experiential learning that takes place in the community or within an organization with or without the presence of a teacher; and as a pedagogy that places the primary responsibility of learning on the learner, with the teacher's primary role being to create opportunities and environments that foster independent and collaborative student learning. Starting with a brief review of the relevant theory – such as andragogy, inquiry-based learning, experiential learning and theories that specifically relate to distance education – she addresses the practicalities of planning a hybrid course, considering class characteristics such as size, demographics, subject matter, learning outcomes, and time available. She offers criteria for determining the appropriate mix of face-to-face, online, and experiential components for a course, and guidance on creating social presence online.

HONORS AND AWARDS

Exemplary Online Adjunct Faculty Award 2019
Brigham Young University – Idaho

SPOT Recognition Award for Work on Educational Technology Tool Development Oct 2018
Utah Valley University

Office of Teaching and Learning Employee of the Quarter May-Aug 2018
Utah Valley University

PACE Distinguished Employee of the Year Award 2017
Utah Valley University

Office of Teaching and Learning Employee of the Month Dec 2016
Utah Valley University

Track Coach of the Year 2012
Western Idaho Conference-1A Division

Cross-Country Coach of the Year 2010
Idaho District III 1A/2A

Hall of Fame – Religious Organizational Leader of the Year 2005-2006
Boise State University

Shawn Marti Scholarship (1 year) 2004-2005
Boise State University

J. Young Memorial Math Scholarship (1 year) 2004-2005
Boise State University

McConkie Scholarship (2 years) 2000-2001, 2004-2005
Boise State University

Laura Moore Cunningham Scholarship (4 years) 2000-2001, 2003-2006
Boise State University

Math Department Scholarship (1 year) 2000-2001
Boise State University

Shoshone Educational Foundation Scholarship (1 year) 2000-2001
Boise State University

PROFESSIONAL AND ACADEMIC MEMBERSHIPS

American Educational Research Association (AERA)	2017-current
Association for Learning Technology (ALT)	2017-current
Educause	2015-current
Online Learning Consortium (OLC)	2013-current
National Council of Teachers of Mathematics (NCTM)	2007-current
Utah Council of Teachers of Mathematics (UCTM)	2015-current
Idaho Council of Teachers of Mathematics (ICTM)	2007-2012

LANGUAGES

English	native language
Spanish	professional working proficiency