STRENGTHS-BASED ANALYSIS OF STUDENT SUCCESS IN ONLINE COURSES

By

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Abstract

The purpose of this research was to increase understanding of post-secondary student success in online courses by evaluating a contextually rich combination of personal, circumstantial, and course variables. A strengths-based perspective framed the investigation. Mixed-method data were collected and analyzed sequentially in three phases: two phases of quantitative collection and analysis were followed by qualitative interviews and comprehensive analysis.

The study first used logistic regression to analyze existing data on more than 27,000 student enrollments, spanning a time period of four academic years. The second phase of research enhanced the modeling focused on a subset of the total population; students from a single semester were invited to complete an assessment of non-cognitive attributes and personal perceptions. Between the two phases, 28 discreet variables were analyzed. Results suggest that different combinations of variables may be effective in predicting success among students with varying levels of educational experience. This research produced preliminary predictive models for student success at each level of class standing.

The study concluded with qualitative interviews designed to explain quantitative results more fully. Aligned with a strengths-based perspective, 12 successful students were asked to elaborate on factors impacting their success. Themes that emerged from the interviews were congruent with quantitative findings, providing practical examples of student and instructor actions that contribute to online student success.

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Chapter 1: Introduction

Enrollment in online courses at degree-granting higher-education institutions within the United States (U.S.) has grown at an exponential rate since the turn of the century (Allen & Seaman, 2013; Allen, Seaman, Poulin, & Straut, 2016). Technological advances, creating the ability to access course content anywhere at anytime, have given a broader, more diverse population access to higher education (Herbert, 2006; Layne, Boston, & Ice, 2013). A number of higher education institutions have turned to online education as a strategy for attracting new students (Clinefelter & Aslanian, 2016). Meanwhile, fewer campus-based students take face-to-face classes exclusively without including one or more online courses in their class schedules (Allen & Seaman, 2017). More than 60 percent of chief academic leaders consider online education critical to their institution's long-term strategy; these institutions continue to expand online programs even as on-campus enrollments decline (Allen et al., 2016).

Despite rapid enrollment growth and institutional acceptance, many academic leaders express concern over poor retention rates among online students (Allen & Seaman, 2013; Berge & Huang, 2004; Park & Choi, 2009). Statistics for online course completion are not collected at the national level. However, scholars consistently claim completion rates among online and distance courses to be significantly lower than for face-to-face courses (Boston, Ice, & Gibson, 2011; Jaggars & Xu, 2010; Lokken, 2017; Rovai, 2003).

Background

Between fall 2002 and fall 2011, the compound annual growth rate for U.S. students taking at least one online course was 17.3% (Allen & Seaman, 2013). Growth in online education across the U.S. not only coincided with technology advances, but with a shift in the number and type of students seeking higher education. Students who enter college immediately after high school, live on campus, and attend full-time in pursuit of a four-year degree are categorized as *traditional* students (Soares, 2013). Bean and Metzner (1985) documented a trend, beginning around 1980, of increased attendance by *non-traditional students*, characterized as older, part-time students who commute to campus. A white paper produced by the National Adult Learner Coalition (2017) asserts that traditional students are no longer the norm; most students enrolled in higher education in the U.S. today are, in fact, non-traditional students. The National Center for Education Statistics (NCES) confirms, “about 74 percent of all 2011-12 undergraduates had at least one nontraditional characteristic” (Radford, Cominole, & Skomsvold, 2015, p. 1).

The shift in university populations—from a predominantly traditional student base to largely non-traditional student base—was spurred by a combination of factors. Growth in the number of non-traditional students seeking higher education may be at least partially attributed to individuals’ desire for higher wages. A report released by U.S. Secretary of Education Margaret Spellings in 2006 recognized post-secondary education as the primary vehicle for socio-economic mobility. Individual economic advancement, however, was not the only factor driving more non-traditional students to enroll. Over the past ten years, an increasing number of Americans have been encouraged to complete post-secondary degrees based on predictions that more jobs in the emerging knowledge economy will require higher education (Carnevale, Strohl, & Smith, 2009; Soares, 2013). Lumina Foundation, an independent, private education foundation, has focused on promoting increased academic attainment, noting that America lags behind global competitors in post-secondary degree completion (Lumina Foundation, n.d.). In response to the perceived national need, as well as recognition for the economic benefit to individual citizens, Lumina articulated a goal for 60% of Americans to earn post-secondary credentials by the year 2025 (Kelderman, 2013).

The public policy push for a greater number of citizens to pursue higher education has unfolded concurrently as online courses have gained traction in academia as an acceptable alternative to the classroom. Online learning removes two barriers that formerly limited access to higher education. First, it removes the barrier of distance. Second, online learning allows for *time shifting* (Allen et al., 2016). The notion of time shifting helps students fit higher education into their schedules, whether they are geographically separated from campus or not. Face-to-face courses require students to meet in a specific place at specific times each week. For students within commuting distance of the campus, the meeting time may be incompatible with work schedules or other obligations. By contrast, online courses generally allow students to engage in learning at a time of day that is convenient for them (Daymont, Blau, & Campbell, 2011). This type of schedule flexibility is an important feature of online courses because, as Joo, Joung, and Sim (2011) observed, online learners often have obligations that compete with their educational priorities.

Students confirmed the need for flexible university alternatives during interviews conducted as part of this study. One student related,

> I was taking [an online course] when my daughter was born, so I started the course a week before she was born and then continued it as she was a tiny

newborn. That was amazing. That was so wonderful to have that flexibility that I could still be a student and still finish the program but also from the comfort of my own home while taking care of my new baby.

Another student said, "I was also working full time, so I took the online course as a way to concentrate on the homework and the course in general after work, and I didn't have to miss anything to go to classes."

The national impetus for higher educational achievement, exemplified by Lumina's "Goal 2025," has permeated to state and local policy goals. Alaska is one of 38 states that recently adopted ambitious goals for higher-education attainment (Kelly, 2013). The Alaska Postsecondary and Completion Network was formed in 2015, with a stated aim to "increase the percentage of the adult population with a postsecondary credential and/or degrees from 47% to 65% by 2025" (Alaska CAN, n.d.).

In a 2013 white paper describing the strategic direction for the University of Alaska (UA), then President Patrick Gamble asserted that the university and state lawmakers both want "a systematic reduction of institutional barriers so that Alaskan students can easily and cost effectively transition into, through, and out of higher education" (Gamble, 2013, p. 3). Gamble acknowledged local demand for course offerings that accommodate the schedules of working students. To that end, expanding online course offerings provides flexibility to meet the needs of non-traditional students based in Alaska. The university has an obligation, according to Gamble, to continually evaluate and upgrade the educational environment to provide for student success (Gamble, 2013).

Distance education has long been important to the state of Alaska. Geographically, Alaska is the largest state in the U.S.; its population is widely distributed, averaging one person per square mile (U.S. Census Bureau, 2010). Furthermore, much of Alaska is inaccessible by road. Traveling to areas off the road system requires another means of transportation, such as plane or boat. Commuting to a campus is not a viable option for many residents. Because of the vast geographic dispersion of residents, correspondence courses (in which students transmitted completed lessons to an instructor via postal mail or email) were popular in the state for decades. Over the past fifteen years, correspondence courses have been replaced by the more robust affordances of online education.

Alaska's widely distributed population makes it an ideal choice for the study of online student success. Rich diversity in cultural backgrounds is an additional advantage of this population. Roughly 25% of UA's online and distance students identify themselves as having a minority background (University of Alaska, 2013). Results of research conducted in this study provide important insights for the Alaskan populace by examining the issues of online success from an Alaska-contextualized vantage point. These results may prove valuable for other populations as well.

Statement of the Problem

Higher education is faced with a dilemma as increasing numbers of students enroll in online courses despite the prospect that they may not complete them. This represents a waste of resources for both the student and the institution (Simpson, 2006). It is, therefore, essential that colleges and universities understand issues related to student attrition and find ways to improve persistence in online courses (Ekstrand, 2013; Herbert, 2006).

Rovai (2003) noted that online students have different characteristics and needs than traditional learners. While a significant body of research has been conducted on student retention over the past seventy years, online retention is a relatively new research area (Berge & Huang, 2004), and research on the stratification of those classified as non-traditional is sparse (Layne et al., 2013).

Tinto's (1975) theoretical model was the first to claim that students' decision to drop out of higher education was heavily weighted by student-to-institution fit. Other theorists built on this notion, emphasizing that student retention is contextually sensitive (Berge & Huang, 2004; Rovai, 2003). While retention often focuses on students' persistence to attain a degree, a more granular level of academic achievement is marked by successful completion of individual courses. It follows that a contextually framed study of student success at the course level will contribute to the larger understanding of online academic attainment. A review of academic journals revealed no empirical research regarding variables that promote student success in online courses within the state of Alaska.

Purpose of the Study

The purpose of this study was to increase understanding of variables that predict or contribute to student success in online courses within the state of Alaska. The research design used a strengths-based perspective and mixed methodologies to develop a more comprehensive understanding of the reciprocal ecology among factors (Maton et al., 2004). The goal of this analysis was to identify factors associated with student success, with an ultimate goal of supporting persistence and increasing educational attainment. The highly distributed nature of the Alaskan population provided access to a diverse set of students for identification of common themes and characteristics. An improved understanding of the factors that affect student success will help policymakers and administrators ensure institutional effectiveness in lowering attrition (Berge & Huang, 2004).

Significance

The history of online learning is relatively short. During the first decade of this century, online pedagogies evolved as new technologies began to mature. It stands to reason, therefore, that research into student success in the online environment is also in a nascent state. Empirical research has not yet coalesced into a strong body of consistent evidence. Many variables have only been examined in a single study, while those that have been examined in multiple studies have produced conflicting results (Clark, 2013; Wang, Shannon, & Ross, 2013). Moreover, few studies to date have examined objective course outcomes in a comprehensive manner that includes contextual variables in combination with personal characteristics. Further, evidence situated within Alaska is particularly sparse. This study sought to address existing gaps in the literature and add to the developing body of empirical evidence regarding online student success.

Research Questions

1. To what extent do personal variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?
2. To what extent do circumstantial variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?

3. To what extent do course variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?
4. To what extent can a combination of personal, circumstantial, and course variables be used to predict success in asynchronous online courses at the University of Alaska Fairbanks?
5. How do successful online students perceive the impact of personal, circumstantial, and course variables in their educational experience?
6. How do successful online students define their role versus the instructor's role, and how does each role contribute to student success?
7. How have successful online students been able to overcome challenges and persist to completion?

Worldview and Methodology

Aligned within a pragmatic worldview, the impetus for this study arose from a recognized need for increasing completion rates in online courses delivered through the University of Alaska. According to Berge and Huang, "there is a need to develop a holistic approach to the description and study of retention that takes into account the experiences of learners and the unique aspects of the distance learning context" (2004, p. 12). The current study applied both quantitative and qualitative measures in order to understand the problem holistically, as situated within the context of Alaska.

In academic circles, differences emerge between those who value the scientific method used in quantitative studies and those who value descriptive context provided by qualitative methodology. Chief among the strengths of quantitative methods are precision and efficiency when working with large groups. By contrast, the primary strengths of qualitative methods lie in their ability to provide contextual, in-depth understanding, rich with detail (Griffin & Museus, 2011).

Over the past two decades, a growing number of researchers have chosen to mix quantitative and qualitative methods within the same study. The pragmatic worldview advocates the advantages of mixed-methods research (Creswell, 2011). According to Plewis and Mason (2005), researchers with a pragmatic worldview are interested in both *what* and *why*: not only an estimate of effect, but also an understanding of why variability exists. The current study used an *explanatory sequential* design. By definition, an explanatory sequential design begins with quantitative measures and follows up with qualitative (Creswell, 2011). In this study, quantitative methods were used to investigate which Alaskan students were most successful in online courses; qualitative interviews with successful students followed. Using a strengths-based approach, the interviews asked participants to describe in their own words how they were able to succeed—either because of or in spite of personal, circumstantial, and course variables. Quantitative and qualitative data were connected for comprehensive analysis.

Limitations

Berge and Huang (2004) claimed that contradictory research evidence regarding student success often results from the unique combination of variables at a specific institution. To minimize the impact of extraneous variables, this research was limited to a single institution. As a result of this limitation, findings may not be generalizable to other populations. The study might be replicated at other universities to test whether results are more widely applicable.

Ethical Assurances and Institutional Acknowledgements

As Director of eLearning at UAF, this author has an interest in the success of online students at the university. Care was taken to ensure that the researcher's role within the university did not inadvertently skew the data, analysis, or interpretation. UAF's Provost, Susan Henrichs, granted permission for using data from the university's information system. The UAF Institutional Research Board (IRB) approved protocols for the research. UAF Planning, Analysis, and Institutional Research (PAIR) assisted with data collection for Phase One to ensure accuracy of the dataset extracted from the university's information system. Dr. Barbara Adams, a member of the candidate's graduate committee, served as Principal Investigator for this study and provided oversight for analyses. Regular meetings with other graduate committee members afforded additional checks and balances to ensure the highest quality of ethical conduct.

Summary

A majority of post-secondary universities in the U.S. have embraced online learning as part of their long-term strategy. Further, enrollment in online courses continues to grow, even as on-campus enrollments decline (Allen & Seaman, 2017; Poulin & Straut, 2016). Despite this apparent enthusiasm for online learning, institutional leaders express concern over retention in these courses and programs.

Campaigns promoting the need for more Americans to participate in higher education have sprung up both at national and at state levels, prompting more non-traditional students to enroll in post-secondary courses. In fact, more than 70% of undergraduate post-secondary students can now be classified as non-traditional (Radford et. al, 2015). Some of the growth in online courses may likely stem from the growing percentage of non-traditional students who are seeking higher education credentials. Non-traditional students, in particular, seem drawn to online courses due to the flexible nature of these offerings (Lee & Choi, 2011; Park & Choi, 2009).

While student retention, persistence, dropout, and attrition have been studied within academia for years, studies specific to online learning are relatively new. More importantly, results of empirical studies on online retention and success have yielded conflicting evidence. The second chapter of this dissertation presents a review of existing literature on success in online courses.

The current study employed a strengths-based, explanatory sequential design to explore student success in online courses at the University of Alaska Fairbanks. Chapter Three provides full details of the methods used to conduct this study, while Chapter Four presents results of the investigation. Finally, Chapter Five summarizes findings for the seven research questions that guided this study. Discussion in the final chapter includes alignment with prior research, implications for practice, and recommendations for additional research.

Chapter 2: Literature Review

Enrollment in online learning continues to grow at a rapid pace. The majority of U.S. universities have integrated at least some online courses into their class schedules, considering online education to be an important part of their strategy for retaining market share (Allen et al., 2016). Despite the continued proliferation of online offerings, concern over attrition in online learning persists (Allen & Seaman, 2013; Park & Choi, 2009).

For 13 years, from 2002 to 2015, the Babson Survey Research Group conducted an annual survey of chief academic officers at degree-granting higher education institutions in an attempt to answer fundamental questions about online education in the United States. The sampling frame for Babson's annual surveys included public, private for-profit, and private non-profit institutions across the U.S. (Allen et al., 2016). In later years, the annual report of the Babson Survey Research Group made key changes to prior practice. First, the report began to utilize data collected through the U.S. Department of Education's Integrated Postsecondary Education Data System (IPEDS) rather than relying on surveys of chief-academic officers for enrollment data. Second, the reporting language shifted from "online courses" to "distance courses," adopting IPEDS definitions. IPEDS provides the most comprehensive data available for all federal-financial-aid-eligible institutions (Poulin & Straut, 2016). The final report of the Babson series (Allen et al., 2016) documents continued growth in distance education enrollments. Nevertheless, the change in data source and definitions introduced slight longitudinal shifts. Therefore, the enrollment numbers that follow are drawn from Babson's 2013 report.

Babson's January 2013 report, based on responses from 2,820 colleges and universities, documented sharp growth in the number of online students. Rising from 1.6 million in fall 2002 to 6.7 million in fall 2011, the compound annual growth rate for students taking at least one online course was 17.3%, compared to just 2.6% for higher education enrollment overall (Allen & Seaman, 2013). The same report documented widespread concern over the retention rates of online courses, with 73.5% of chief academic officers agreeing that lower retention rates in online courses were an important or very important barrier to the growth of online instruction. As Boston and colleagues (2011) noted, student retention is important both for the individual student and for the health of the institution.

Based on a review of relevant scholarship, Glazier (2016) described three broad categories of explanations for the lower success rates of online courses compared to classroom courses: 1) student characteristics, including both demographics and academic preparedness; 2) the student's environment; and 3) course design and interaction. This review explores research in each of those categories.

Key Terms

In preface to the literature review, this chapter first defines key terms based on widely accepted definitions from the scholarly literature. The theoretical background for retention and attrition in higher education is summarized, with discussion of the models developed for traditional, non-traditional, and online students. Finally, parameters for inclusion in the current review are described.

Online Courses

Online courses are delivered via the Internet. Students can typically complete online courses from any geographic location, as long as they have a reliable Internet connection. The IPEDS definition for distance education—composed largely of online courses—emphasizes “regular and substantive interaction between the students and the instructor” (Allen et al., 2016). Online courses may either be delivered *synchronously* or *asynchronously*. Synchronous online courses include predetermined meeting times. Students do not have to be in the same location, but must meet online at a specified time. By contrast, asynchronous courses do not require same-time online meetings. Instead, they facilitate student-to-student and student-to-instructor interaction via a range of Internet technologies (e.g., discussion forums, web sites, social networking technologies, email). Asynchronous online courses afford students flexibility in time as well as place. (Daymont et al., 2011; Olson & McCracken, 2014).

Retention and Persistence

Research literature has used a variety of terms to describe students’ continued pursuit and eventual attainment of educational goals. Two of the terms most commonly used are *retention* and *persistence*. Berge and Huang (2004) defined *retention* as “continued student participation in a learning event to completion” (p. 3). Similarly, Rovai (2003) defined *persistence* as continued action in spite of obstacles. As related to higher education, persistence indicates a student’s decision to continue in a course or program of study, usually with the ultimate goal of earning an academic credential. Unlike elementary and secondary education, where attendance is mandatory, participation in post-secondary education is a matter of choice. It is important to note that an adult's decision to persist in higher education may be influenced by external circumstances as well as factors related to the course, degree program, or academic institution (Park & Choi, 2009; Rovai, 2003).

Attrition

In contrast to retention and persistence, *attrition* indicates discontinuation or departure from an academic program of study prior to completion. At the course level, attrition may be operationalized by *withdrawal:* a status in the student's academic record indicating he/she is no longer actively enrolled in the course. At the program level, the term *stop out* is used to identify students who leave but later return to complete a degree. By contrast, individuals who *drop out* leave an academic program and do not return (Tinto, 1993).

Theoretical Models

Researchers have explored the issues of persistence, retention, and attrition in higher education for decades looking for factors that reliably predict which students will complete a course or program and which will not (Herbert, 2006). Early models were drawn from psychological perspectives (Rovai, 2003; Tinto, 1993). For example, student motivation has long been considered an important factor in student persistence. A number of constructs for learner motivation have been derived from psychological theoretical models (Yukselturk & Bulut, 2007). Many motivational theories propose that motivation is highly related to expectancy beliefs (Pintrich & Schunk, 1996). People are motivated to action or inaction based on their beliefs about what outcome—if any—will result from their actions. Outcome expectancies influence how much effort students are willing to expend, how long they are willing to persevere, and how resilient they will be when encountering setbacks (Bandura, 1991; Pajares, 1996; Schunk, 1991).

Tinto (1987, 1993) criticized psychological theories of retention for placing too much weight on the ability and willingness of individual students. In other words, he believed psychological models framed student attrition solely as a shortcoming, weakness, or personal failure of the student. Tinto claimed failure to meet academic standards accounted for only 25% of student attrition. He proposed three additional factors as highly influential in students' decision to leave college: adjustment (socially and intellectually), incongruence (student mismatch with the institution, both academic and social), and isolation (Tinto, 1993). His widely cited theoretical model of student dropout, originally published in 1975, was grounded in earlier psychological models, but conceptually distinct in its focus on student-to-institution fit (Rovai, 2003; Tinto, 1975).

Non-Traditional Students

Examining the distinctions between non-traditional and traditional students, Bean and Metzner (1985) questioned whether previous models were adequate to explain attrition among non-traditional students. The distinction between traditional and non-traditional is not a simple dichotomy amenable to easy definition. The criteria used by Bean and Metzner (1985) included some combination of three factors: those who are age 25 or older, reside off campus, and/or attend part-time rather than full-time. Perhaps most importantly, Bean and Metzner note that non-traditional students have a social network outside the university and are not primarily influenced by the school's social environment. Non-traditional students tend to be more interested in academic offerings than immersion in university culture (Bean & Metzner, 1985). While Tinto (1975) asserted the most critical variable in persistence was student integration into academic and social systems of the college, Bean and Metzner argued that non-traditional students were not particularly interested in social aspects of college life and therefore were more heavily influenced by factors outside the institution (Bean & Metzner, 1985).

Online Students

While Tinto's (1975) model focused on traditional students and Bean and Metzner's (1985) model focused on non-traditional students, both addressed attrition among post-secondary students who physically attended classes on campus. Neither dealt with the unique characteristics and constraints of online students. Rovai (2003) attempted to address this theoretical gap with a composite model for online attrition that synthesized elements of Tinto's model with Bean and Metzner's work, and additionally incorporated skills required of online students: computer literacy, information literacy, time management, and interpersonal communication skills. His model included a timeline aspect, separating the student characteristics and skills that exist prior to admission from internal and external factors that impact student persistence after admission (Rovai, 2003).

Following an extensive review of prior research and theoretical studies, Berge and Huang (2004) created a sustainable model that categorized student retention factors into three clusters: personal variables, institutional variables, and circumstantial variables. Their model was intended to be open-ended and inclusive, built as a framework that would allow institutions to add variables to the three clusters and to prioritize the relative importance of the three areas within the institutional context (Berge & Huang, 2004). A review of the literature did not reveal any theoretical models of online student retention published since Berge & Huang's model.

Previous Reviews

Lee and Choi (2011) examined scholarly research published between 1999 and 2009, looking for empirical data on variables that influenced students' decision to drop out of post-secondary online courses. They identified 69 factors, grouped into three broad categories: student factors, course/program factors, and environmental factors. The three categories identified by Lee and Choi (2011) align with Berge and Huang's (2004) theoretical framework.

In contrast to Lee and Choi's (2011) focus on dropout, Hart (2012) conducted an integrated literature review of articles published between 1999 and 2011 focused not on dropout, but on students' ability to persist in online courses. Hart noted that persistence is a complex variable that may not be directly related to knowledge acquisition at all. A student's decision to persist may be influenced by a combination of factors both internal and external to the university.

As a complement to both reviews described above, this literature review focuses on student *success* in online courses. Shushok and Hulme (2006) noted, "we have largely neglected to ask ourselves in any serious and organized manner what it is within an individual student that creates success" (p. 5). This review expands on Hart's (2012) review of persistence by examining final grades in addition to course completion. Among research studies initially considered for review, student success was defined in a variety of ways: course completion, defined level of final course grade (which varied between studies), continued enrollment in an academic program, completion of an academic credential, and/or student satisfaction. The current study examines student success at the course level. Therefore, the literature review was narrowed to examine studies of course completion and final course grade. As Puzziferro (2008) notes, the use of final grade is not a perfect measure of student learning, but it does have practical meaning as a measure of academic success, because it typically signifies approval for moving to the next level.

Criteria for Inclusion

This literature review was limited to studies published in peer-reviewed academic journals over the past ten years (2007–2016). The two literature reviews cited above covered a timeframe beginning in 1999 and ending in 2009 and 2011, respectively. Both technology and the pedagogy used for online teaching have evolved since 1999. Allen et al. (2016) spoke to the maturation of online programs in their 2016 report. The past decade provides a rational time boundary for evaluation of success in modern online courses. Databases used to locate applicable research included Academic Search Premier, ED Full Text (Wilson), ERIC, and PsycInfo. Only studies of fully online courses were considered. Studies pertaining to face-to-face courses or blended courses (in which only part of the course was completed online) were excluded.

As previously mentioned, this study addressed success at the course level, not program completion or even persistence from year to year within a program of study. While the ultimate goal of post-secondary education is the achievement of an academic credential, such success is achieved one-step-at-a-time by the completion of individual courses. Further, student motivation and learning strategies may vary based on the subject matter and difficulty of a specific course (Duncan & McKeachie, 2005). Therefore, the research included here was restricted to studies of course-level outcomes. Massive Online

Open Courses (MOOCs) were excluded from the review, as they typically do not lead to traditional post-secondary degrees. MOOC participants are usually not registered as students of the school and do not receive college credit for completion (Allen et al., 2016).

Because the goal was to understand factors that promote success in online courses—not to compare online delivery against other forms of course delivery—studies that compared face-to-face results to online results were excluded. Studies were only included if the outcome variable was an objective measure of course completion, final course grade, or some other comprehensive evaluation of course scores. Studies that used other measures of success as a dependent variable, such as perceived learning or student satisfaction, were excluded given the greater subjectivity of these measures. However, studies that included student satisfaction and perceived learning as independent variables—in other words, when they were evaluated as factors that might predict course completion or passing grade—were included.

Studies of student behavior during the course (such as data analytics that tracked frequency of student log-ins) were excluded since these variables do not align with the antecedents of success framework of student characteristics, course characteristics, and student circumstances.

Overview of Selected Research

Thirty-two empirical studies were selected for inclusion in this review. Published results included diverse combinations of 94 different variables. Conflicting evidence was presented regarding the relationship between specific variables and course outcomes. Nearly half the variables examined failed to produce statistically significant evidence in any of the 32 studies. This review will primarily address the variables that demonstrated significance in at least one study.

The review included studies from public as well as private institutions; from community colleges and from universities; from the U.S., Sweden, Turkey, Northern Cyprus, and Korea. Population samples in some studies were limited to a specific educational level, discipline area, or even a specific course, while other studies examined a broad range of participants.

Organization of the Review

For this review, Berge and Huang's (2004) model served as a framework to organize the variables under examination. Because 94 variables proved unwieldy for display and discussion, variables were grouped into eight subcategories, which were then grouped according to Berg and Huang's framework (i.e., personal variables, circumstantial variables, course variables). Table 2.1 provides a list of reviewed articles and identifies the subcategories of variables evaluated in each study. All 32 studies are referenced briefly in the narrative, but the discussion focuses on areas where research results were statistically significant.

Table 2.1 Summary of reviewed studies.

			Personal Variables				Circumstantial Variables		Course Variables	
Author(s)	Date	*n*	Demographics	Acad. Performance	Non-Cognitive Attributes	Student Strategies	Academic Circumstances	Non-academic Circumstances	Course Characteristics	Student Perceptions
Aragon & Johnson	**2008**	**305**	■	■		■	■	■		
Bälter et al.	2013	493	■			■				
Baturay & Yukselturk	2015	148	■		■			■		■
Cochran et al.	2014	2,314	■	■			■	■		
Fair & Wickersham	2012	194		■	■					
Garman	2010	235		■						
Gibson et al.	2010	14,987	■							
Glazier	2016	465							■	■
Guidry	2013	163	■	■			■			
Hachey et al.	2012	962					■			
Hachey et al.	2014	962		■			■			
Harrell & Bower	2011	225	■	■	■		■	■		
Hegeman	2015	95							■	
Jaggars & Xu	2016	678							■	■
Joo et al.	2013	897			■					■
Jost et al.	2012	320	■	■						

Table 2.1 continued

			Personal Variables				Circumstantial Variables		Course Variables	
Author(s)	Date	*n*	Demographics	Acad. Performance	Non-Cognitive Attributes	Student Strategies	Academic Circumstances	Non-academic Circumstances	Course Characteristics	Student Perceptions
Kupczynski et al.	2014	959	■							
Lee et al.	2013	169			■	■				
Levy	2007	133	■	■	■		■	■		■
Liu et al.	2009	108								■
Nichols & Levy	2009	145		■	■				■	
Olson & McCracken	2014	36							■	
Park & Choi	2009	147	■				■	■		■
Puzziferro	2008	815			■	■				
Rakap	2010	46		■	■		■			
Rockinson-Szapkiw et al.	2016	131	■						■	■
Rogers	2015	243			■					
Suphi & Yaratan	2012	99	■	■	■	■		■		
Wadsworth et al.	2007	89	■		■	■				
Wang et al.	2013	256	■		■	■	■			■
Yen & Liu	2009	108				■				
Yukselturk & Bulut	2007	80	■		■	■	■			

Personal Variables

The majority of studies in this review included personal student characteristics among the independent variables. Personal information (demographic variables, as well as information related to the student's past academic performance) is routinely collected at the time of admission to post-secondary institutions; this information could be used to enhance advising practices if connections were found between these factors and student success (Jost, Rude-Parkins, & Githens, 2012). Across the studies in this review, the large and diverse set of personal variables was sorted into four distinct subcategories: demographics, academic performance, non-cognitive attributes, and student strategies.

Demographics

Age and gender were the most frequently investigated student characteristics in these studies. Race, ethnicity, and/or nationality were examined in several studies; military status was included in one investigation; and residency (e.g., U.S. student, international student) was considered in one study.

Studies of demographics yielded mixed results. The majority of studies included in this review showed no significant difference in course outcome based on age or gender (Baturay & Yukselturk, 2015; Gibson, Kupczynski, & Ice, 2010; Guidry, 2013; Harrell & Bower, 2011; Jost et al., 2012; Levy, 2007; Park & Choi, 2009; Yukselturk & Bulut, 2007). Four of seven studies found no correlation between race or ethnicity and online course success (Aragon & Johnson, 2008; Gibson et al., 2010; Harrell & Bower, 2011; Jost et al., 2012). Military status was inconclusive and residency was not shown to be significant. The following paragraphs summarize studies that found significant results for age and gender.

Age. Age was frequently hypothesized as a discriminating factor for success in online courses under the assumption that older students might be less comfortable with the technology medium. Although that notion seems plausible, only two of 12 studies revealed any association between age and success, and results of those two studies were dissimilar. Suphi and Yaratan's (2012) research on 99 undergraduate students in Turkey found a negative correlation between age and final course grade, as hypothesized. On the other hand, Cochran, Campbell, Baker, and Leeds' (2014) study of 2,314 undergraduate students at a large state university in the U.S. revealed the opposite—a positive correlation between age and course completion for two subgroups. Among students who did not receive scholarships and among those without student loans, older students were less likely to withdraw than younger students (Cochran et al., 2014). Among other subgroups, Cochran et al. (2014) did not find a significant association between age and online course completion. In summary, this review of 32 studies yielded only minimal evidence for age as a predictor of online success.

Gender. Aragon and Johnson (2008) found a weak correlation between gender and completion at the community college level, with females completing at a higher rate than males. Rockinson-Szapkiw, Wendt, Wighting, and Nisbet (2016) found that the combination of gender and ethnicity accounted for 6.9% of variance in final course scores of graduate students enrolled in educational technology courses. Two studies discovered gender to be significant for specific subgroups, although not significant for the entire population. First, in a study of undergraduate Education majors, Kupczynski, Brown, Holland, and Uriegas (2014) found gender to be significant in the prediction of final course grade among students with low grade point averages (GPAs), but not among students with higher GPAs. Among the group with low GPAs, females achieved higher final course grades than males (Kupczynski et al., 2014). Similarly, Cochran and colleagues (2014) found that gender correlated with course completion among non-seniors and students without loans; among those groups, females were less likely to withdraw than males. Thus, among 16 studies that examined gender for correlation with success, four produced significant results. In three of the four studies, females were shown to have more positive correlation with success than males. By contrast, Rockinson-Szapkiw et al.'s (2016) study showed males to have higher course points than females. Differences in these results may have been influenced by additional factors within the sample populations. As noted, Rockinson-Szapkiw and colleagues (2016) examined graduate students while Aragon and Johnson (2008) studied community college students. Further, Rockinson-Szapkiw et al.'s (2016) research was restricted to educational technology courses. The fact that two studies revealed gender as a significant factor for some groups but not others (Cochran et al., 2014; Kupczynski et al., 2014) reinforces the notion that other aspects, in addition to gender, may have contributed to the findings.

Race. Seven studies investigated whether race, ethnicity, or nationality correlated with successful student completion in online courses. Three of the seven produced significant results. As noted above, Rockinson-Szapkiw et al. (2016) reported significant results for gender and ethnicity together. Suphi and Yaratan (2012) included nationality along with four other factors in a model that explained 47% of variance in final course grade. Cochran et al. (2014) found that Black students without student loans were more likely to withdraw from online courses, while Black students who received merit-based scholarships were less likely to withdraw.

Military status and student residency. Only one study considered military status as a factor. Gibson et al. (2010) investigated the relationship between final course grade and student demographics among students at a fully online, for-profit university that serves a large population of military students in addition to civilians. Their large-scale study examined impact of gender, ethnicity, age, and military status among nearly 15,000 undergraduate students. Although all four independent variables showed a significant association with final course grade, the variance explained was so small that Gibson and colleagues (2010) reported the analysis to be inconclusive. Levy (2007) performed the only study from this review that considered residency as a variable (e.g., U.S. citizen or international student). Results for residency were not significant (Levy, 2007).

In short, the relationship between demographic variables and online student success has neither been proven nor disproven conclusively. Evidence for statistical significance of most individual variables is either inconsistent or contradictory. Some studies produced different results for various subgroups. Other studies found that a combination of variables produced statistically significant results. Indications that variables show different levels of significance between subgroups and that combined variables increase predictive accuracy lend credence to the idea that variables should be considered in a more holistic fashion.

Academic Performance

Academic performance is often used as a measure of cognitive skills. Among variables in this review categorized as academic performance, cumulative GPA was the most frequently studied. Notably, cumulative post-secondary GPA produced statistically significant results in six of eight studies. Guidry's (2013) study found evidence for a correlation between course success and prior semester GPA, but did not produce significant results for cumulative GPA. Nichols & Levy (2009) found a significant association between high school GPA and online course success.

Grade point average (GPA). In a study of 225 community college students, Harrell and Bower (2011) found higher cumulative GPA reduced the odds of student withdrawal from online courses. Similarly, Cochran and colleagues (2014) found that students with cumulative GPAs of 3.0 or higher were less likely to withdraw than students with lower GPAs. However, for a few subgroups, cumulative GPA was not a significant factor; namely, older students, Black students, and students who received Pell Grants (Cochran et al., 2014).

As mentioned in the section on demographics, Suphi and Yaratan's (2012) five-factor model explained 47% of variance in course grade. Cumulative GPA was included in the model along with age and nationality, as already reported. The other two factors—self-efficacy and mother's educational level—will be discussed in greater detail later in this review.

Aragon and Johnson (2008) found that completers of online courses had higher grade point averages than non-completers—although their definition of a completer bears mention. Their study of 305 community college students defined completers as those who earned a final grade of D or higher in at least one online course (even if the same student failed to complete other courses). Aragon and Johnson also found that completers enrolled in more courses than non-completers (2008).

Jost et al. (2012) found initial differences in final course grades among online two-year college students in Kentucky based on age and ethnicity. However, age and ethnicity were not statistically significant after controlling for cumulative GPA. Linear hierarchical multiple regression revealed cumulative GPA as the only significant predictor of online course outcomes, accounting for about 40% of the variance in final course grade.

In a study of 962 students at an urban community college, Hachey, Wladis, and Conway (2014) found that pre-course cumulative GPA was a significant predictor of success (final grade of C- and higher) and also of retention (completion of the course, regardless of final grade). Among students with no previous online course experience, success and retention rates increased linearly with GPA. However, among students with prior online course experience, prior course outcomes were a better predictor of retention and final grades than GPA.

Nichols and Levy (2009) conducted a study of 145 student athletes at a single university to investigate success in online courses among that subpopulation. Results of Nichols and Levy's investigation indicated that high school GPA was a significant predictor of success.

Test scores. In addition to GPA, various academic test scores were examined as possible predictors of online student success. Nichols and Levy included SAT scores in their study of student athletes. They did not find SAT scores to be a significant predictor of successful course completion (2009).

Guidry (2013) used ACT scores to determine whether predictors of student success in a quantitative online course differed from predictors of student success in a qualitative online course. Two courses at a business school were examined: the quantitative course (Financial Management) involved calculations and measurements, while the qualitative course (Principles of Real Estate) focused on conceptual topics, with little or no math required. Success in both courses was defined as a final course grade of C or higher. Interestingly, none of the variables examined were significant predictors of success in both courses. For the quantitative course, ACT Math Scores and prior-semester GPA demonstrated a positive correlation with success. In the qualitative course, only reading comprehension (measured by ACT Reading Score) was found to be a significant predictor of success. The authors noted the size and scope of the study as a limitation for generalization of its findings.

Garman (2010) hypothesized that reading comprehension would impact performance in an online class, based on the idea that online courses entail reading and comprehending complex material without the benefit of face-to-face instructor explanations. Results of the study were mixed. Reading scores were a significant predictor of student success on timed assessments, but a poor predictor of success on other types of assessment (Garman, 2010). This result could be explained by the fact that untimed assignments afford students the opportunity to read more slowly, re-read complex passages, or look up unfamiliar words.

Two studies investigated the impact of student computer skills on course performance and produced conflicting results. In Rakap's (2010) study of 46 teachers who were seeking to add a special education Autism Endorsement to their teaching credentials, a moderately positive correlation was identified between computer skills and student success. Harrell and Bower (2011), on the other hand, found that an increase in basic computer skills among community college students also increased the odds of withdrawal from online courses. They suggested some possible explanations for this unanticipated result, but also acknowledged that it might simply be an anomaly of their sample (Harrell & Bower, 2011).

In summary, among academic performance variables evaluated for association with online success, student GPA (whether collegiate GPA or high school GPA) produced the strongest and most consistent results. Further, GPA was shown significant across diverse institutions—at community colleges as well as universities. In fact, GPA produced more consistent results than any other variable explored in the 32 studies included in this literature review.

Non-Cognitive Attributes

Variables in this review that were categorized as non-cognitive attributes included learning styles, locus of control, several subscales of motivation as measured by the Motivated Strategies for Learning Questionnaire (MSLQ), and various forms of self-efficacy. Because self-efficacy represents an appraisal of one's own capability, it is best assessed within a specific domain (Pajares, 1996). A student might estimate himself/herself to be highly capable in one area, but less capable in another. Studies in this review included variables of academic self-efficacy (Suphi & Yaratan, 2012), computer efficacy (Baturay & Yukselturk, 2015), internet self-efficacy (Baturay & Yukselturk, 2015), mathematics self-efficacy (Wadsworth, Husman, Duggan, & Pennington, 2007), technology self-efficacy (Puzziferro, 2008; Wang et al., 2013), and self-efficacy related to a specific course, as measured by MSLQ (Joo, Lim, & Kim, 2013; Lee, Choi, & Kim, 2013; Wang et al., 2013; Yukselturk & Bulut, 2007). Results related to self-efficacy were mixed; significant results are summarized below.

Self-efficacy. Wadsworth and colleagues' (2007) investigation of 89 high-risk students enrolled in an online developmental math course found evidence for statistically significant relationships between mathematics self-efficacy, student learning strategies, and final course grade. This result lends support for use of a domain-specific test of self-efficacy—in this case, students' perceptions of their own math capability.

Wang et al. (2013) employed structural equation modeling to examine relationships among several factors hypothesized to impact student achievement in online courses. Results of their study suggested that course satisfaction and technology self-efficacy have a direct influence on final course grade, while other non-cognitive attributes and student learning strategies play mediating roles—leading to satisfaction and self-efficacy, thereby contributing indirectly to student success. By contrast, Puzziferro (2008) found no significant difference in technology self-efficacy among final grade comparison groups. Differing results for technology self-efficacy might be attributable to different research methodologies, different assessment instruments, or differences in the populations. Similar to Wang et al. (2013), Joo et al. (2013) also used structural equation modeling to investigate predictors of online achievement. They found course self-efficacy to have a statistically significant impact on final course grade.

Learning styles. Four studies investigated students' learning styles and arrived at conflicting conclusions. Rakap's (2010) study of teachers (also cited in relation to computer skills) revealed that students with the read/write learning style received highest scores, while students with a kinesthetic learning preference received the lowest scores on course quizzes. Likewise, Harrell and Bower's (2011) study indicated that *auditory learning style*, defined as a preference for verbal rather than written instruction, increased the odds of student withdrawal. By contrast, Yukselturk and Bulut's (2007) study of computer-programming students in Turkey did not find a statistically significant variance in student success based on learning styles. Fair and Wickersham (2012) evaluated learning styles, along with personal attributes, reading rate and recall, technical competency, technical knowledge, and typing speed, using a tool called Readiness for Education At a Distance Indicator (READI). Results among 194 students in basic communication courses at two community colleges indicated no significant relationship between the readiness assessment and final course grade.

Locus of control. A total of eight studies examined student beliefs about locus of control: six assessed general locus of control and two focused on academic locus of control. As is true of most other variables in this review, results were mixed. Five of the eight found no significant relationship between course outcomes and locus of control, while three of the eight reported significant results, discussed below.

Rogers (2015) examined whether locus of control had a moderating effect on final course grade among 243 undergraduates enrolled in online courses during a six-year period. Students were asked to complete a Likert scale assessment based on Rotter's (1966) locus of control (LOC) instrument. Resulting scale scores classified participants as either internal LOC or external LOC. Rogers (2015) then used a two-tailed T-test for final course grade to compare mean scores of internal and external LOCs. Results indicated statistically significant performance differences between the two groups, with internal LOCs earning higher course grades.

In a study of 169 Education majors in Korea, Lee and colleagues (2013) compared non-cognitive attributes (self-efficacy and academic locus of control), student strategies (metacognitive self-regulation and time/environment management), and non-academic circumstances (support from family or work) between two groups: those who completed an online course versus those who withdrew. Descriptive Discriminant function Analysis (DDA) revealed that differences in academic locus of control and metacognitive self-regulation were significant between the two groups; means of the other three factors did not differ significantly between those who completed and those who withdrew (Lee et al., 2013).

Motivation. Five of the studies reviewed here used the Motivated Strategies for Learning Questionnaire (MSLQ) to assess non-cognitive student attributes and student learning strategies. In its entirety, the MSLQ is composed of 81 self-reported items scored on a Likert scale. However, it was designed to be modular, allowing researchers to selectively use components or subscales of the instrument to fit their specific needs and interests (Duncan & McKeachie, 2005). The MSLQ is composed of two sections. The first section, which includes six subscales, is based on motivational constructs of expectancy, value, and affect. For purposes of this review, subscales from the motivation section of MSLQ were categorized as non-cognitive attributes. With the exception of course self-efficacy, reported above, the motivation section of MSLQ did not produce evidence of direct impact on course outcomes. The second section of MSLQ is related to learning strategies; it includes nine subscales related to cognitive strategies, metacognitive control, and resource management. For the purposes of this review, learning strategies are considered a separate variable category. Results from the studies that used the MSLQ subscales for learning strategies are discussed below.

Student Strategies

Among nine studies in this review that investigated student strategies, four used some part of the MSLQ to collect data (Lee et al., 2013; Puzziferro, 2008; Wang et al., 2013; Yukselturk & Bulut, 2007). All four studies found evidence of significance for at least one subscale of MSLQ. As previously mentioned, Lee and colleagues (2013) found a statistically significant difference in metacognitive self-regulation between Education majors who completed an online course versus those who withdrew.

Learning Strategies. Puzziferro (2008) used all nine subscales of MSLQ to explore the relationship between self-regulation and final course grade among community college students. In a comparison by final grade, ANOVA revealed mean differences in two of the subscale scores: time and study environment, and effort regulation. A least squares difference post hoc test suggested that students with higher final grades reported better management of study time and environment. Likewise, students who received a final grade of C or higher reported better effort regulation than students who withdrew from the course.

Yukselturk and Bulut (2007) conducted a mixed-methods study from the population of an online computer-programming course offered in Turkey. Their research included interviews with two instructors and quantitative data collected from 80 students.

Yukselturk and Bulut used linear stepwise regression to evaluate more than a dozen factors, revealing self-regulation as the only variable to explain statistically significant variance in student success. For Yukselturk and Bulut's (2007) study, self-regulation was constructed from two subscales of MSLQ: metacognitive self-regulation and effort regulation.

Wang et al.'s (2013) structural equation model, discussed earlier, supports the indirect role of MSLQ constructs of metacognitive self-regulation, time and environment management, elaboration, and critical thinking in online course success. According to the model derived from their study, these specific student strategies lead to higher levels of satisfaction and self-efficacy, which in turn lead to higher course grades among online students.

In summary, based on the studies that measured student learning strategies via MSLQ (Lee et al., 2013; Puzziferro, 2008; Wang et al., 2013; Yukselturk & Bulut, 2007), three subscales had a significant association with course outcomes: metacognitive self-regulation, time and environment management, and effort regulation. Two additional subscales (elaboration and critical thinking) demonstrated an indirect influence on student outcomes. Other studies used measures outside of the MSLQ to examine the impact of student learning strategies, as discussed below.

Wadsworth et al. (2007) found evidence for statistically significant relationships between mathematics self-efficacy, student learning strategies, and final course grade among developmental students. To assess learning strategies, they used the Learning and Study Strategies Inventory (LASSI). Similar to MSLQ, the LASSI diagnostic survey includes a number of subscales. Wadsworth et al.'s (2007) multiple regression analysis revealed the subscales of motivation, concentration, information processing, and self-testing to be significant in predicting final course grade, while six additional subscales did not show a significant relationship to final grade (attitude, time management, anxiety, selecting the main idea, use of support materials, and test-taking strategies).

Bälter, Cleveland-Innes, Pettersson, Scheja, and Svedin (2013) also conducted research among students at the developmental level. Their study included 493 students in Sweden who were enrolled in one of two courses: a mathematics course intended to repeat concepts students had learned over the past 12 years and a programming course designed to introduce a new subject not previously studied. Both were considered preparatory courses for new students in mathematics-intensive programs. Both were delivered in a self-paced, pass/fail, auto-graded format. Bälter et al. (2013) used the Approaches and Study Skills Inventory (ASSIST) to investigate differences between those students who completed (passed) one of the two courses and those who did not. ASSIST identifies three basic student approaches: deep, surface, and strategic. The deep approach is characterized by a search for understanding. By contrast, the surface approach focuses on repetition and memorization rather than understanding. The strategic approach is geared toward academic achievement—with a focus on fulfilling course requirements in an organized and efficient manner. Bälter et al.'s (2013) results indicated that deep approaches to learning were associated with higher pass rates in both courses. Additionally, Bälter and colleagues found that the strategic approach was also positively correlated with success in the math course.

Learning readiness inventories. A number of diagnostic surveys have been developed to assess student readiness for online learning. Examples among studies in this review include MSLQ, LASSI, READI, and ASSIST, as discussed above. Some institutions administer these tests routinely to incoming students. In her doctoral research, Clark (2013) explored online student success and retention by using archived university data on student characteristics, academic performance, and scores on the SmarterMeasures Learning Readiness Indicator. According to Clark, the SmarterMeasures instrument was formerly called READI. Fair and Wickersham's (2012) study, using the READI survey, failed to reveal a significant relationship between the readiness assessment and final course grade. Clark obtained somewhat different results, perhaps based on a difference in population. Clark found a statistically significant association for some of the scales, but noted the scale scores only explained a small percentage of variance in final course grade. GPA produced the strongest relationship with final grade. Clark's results indicated that 44-47% of variance in final course grade could be explained by a combination of GPA, age, and academic placement in remedial Math or English (Clark, 2013). Clark's dissertation was not included among the 32 studies listed in Table 2.1 because it did not meet the criteria of publication in a peer-reviewed journal; nonetheless, it is relevant to this discussion.

Autonomy. Yen and Liu (2009) evaluated learner autonomy as a potential predictor of student achievement at two levels: course success and final grade. Yen and Liu defined autonomy for this study in relation to intentionality of behavior in learning activities. The predictive relationship between learner autonomy and success (defined as a final grade of C or higher) was evaluated via binary logistic regression, while the relationship between autonomy and final grade (including a category for failure and withdrawal) was evaluated by means of ordinal logistic regression. Analyses revealed the odds of course success and of a higher final grade both increased with each unit increase in the learner autonomy score.

Circumstantial Variables

Roughly half the studies in this review included factors related to individual student circumstances. These circumstantial variables were divided into two subcategories: academic circumstances, such as class standing; and non-academic circumstances, such as employment status. Some studies considered both types of variables, while others limited their investigation to one or the other, mirroring theoretical perspectives discussed earlier in this chapter. Recall that Tinto's (1975) attrition model emphasized the importance of student integration within academic systems, Bean and Metzner (1985) stressed the influence of factors outside the university, and Rovai (2003) included both.

Academic Circumstances

Two studies reported class standing as significantly associated with course completion. Three studies evaluated the effect of full-time student enrollment on student outcomes. One study examined success in prior online courses for association with success in a current course.

Class standing. Based on research from face-to-face courses, Cochran et al. (2014) developed and tested eight hypotheses for the relationship between online course withdrawal and individual student characteristics. Their study included more than 2,300 undergraduate students at a large state university. Cochran et al. found that senior class standing and high GPA were significantly related to retention among all students, while other variables were only significant for certain subgroups. Across all students, seniors were less likely to withdraw from an online course than non-seniors. Among certain subgroups, students who had previously withdrawn from online courses were more likely to withdraw in the current term, although among younger students and students with high GPAs, previous withdrawal was not a significant factor (Cochran et al., 2014).

Levy (2007) used one-way ANOVA and non-parametric Mann-Whitney tests to compare characteristics of 108 students who completed online courses against characteristic of 25 students who dropped from online courses at a state university. Levy (2007) found significant differences between completers and non-completers for the factors of satisfaction with the course, class standing, and time to graduation (e.g., number of semesters remaining until the student expected to graduate). The small size of this study (especially in the number of students who dropped) was a limitation.

Full-time versus part-time enrollment. Three studies evaluated full-time versus part-time student enrollment. Two of the three found no evidence that a student's credit load impacted course outcomes. However, as reported in the section on GPA, Aragon and Johnson (2008) found that students who earned a final grade of D or higher in at least one online course enrolled in more online credit hours than non-completers. Further, completers enrolled in more hours overall (regardless of delivery mode) than non-completers (Aragon & Johnson, 2008).

Prior online success. Hachey et al. (2014) found that pre-course cumulative GPA was a significant predictor of course success and retention. However, the primary purpose of their study was to compare the predictive value of GPA against the predictive value of prior online course outcomes. In an earlier study using the same data, they found that previous online experience was not a good predictor of success unless previous success or failure was identified as well (Hachey, Wladis, & Conway, 2012). Therefore, in the 2014 study, they included an analysis of whether each student achieved a final grade of C- or better in all previous online courses attempted (Hachey et al., 2014). Results showed that, among students with prior online course experience, prior courses outcomes were a better predictor of retention and final grades than GPA. It is important to note that Hachey et al. (2014) did not consider students who had mixed success in previous online courses (i.e., some success, some non-success), but only students who were either successful in all or unsuccessful in all previous attempts.

Non-Academic Circumstances

Few of the studies on non-academic circumstances revealed a significant association with online course outcomes. Four variables were shown significant in a single study: (a) reason for taking courses online (Baturay & Yukselturk, 2015), (b) support from family and work (Park & Choi, 2009), (c) students' use of loans (Cochran et al., 2014), and (d) parents' educational level (Suphi & Yaratan, 2012).

In a study of 148 students taking an online English Language course in Turkey, Baturay and Yukselturk (2015) discovered only one variable with a significant correlation to final exam scores: the student's stated reason for choosing to take the course online. Park and Choi's (2009) analysis of 147 non-traditional students taking job-related online courses at a Midwestern university found significant differences between completers and dropouts in perceived family and organizational support.

Cochran et al. (2014) hypothesized that students with loans would be less likely to withdraw than students without loans; their results revealed the opposite. Among roughly half the subgroups in their study, Cochran and colleagues (2014) found that students with loans were more likely to withdraw from an online course than students without loans. Of the 99 students from Turkey and Northern Cyprus included in Suphi and Yaratan's (2012) study, students whose mothers had lower levels of education received higher grades. This result was counterintuitive. Suphi and Yaratan (2012) commented that the effect of mother's educational level was unexpected and worthy of further investigation.

Students' employment status was investigated in three different studies, but not found significant in any of the three (Baturay & Yukselturk, 2015; Harrell & Bower, 2011; Levy, 2007). Marital status and number of children were also evaluated by Harrell and Bower (2011), again without significant results.

Course Variables

For purposes of this review, course variables have been divided into two subcategories: 1) course characteristics as evaluated and reported by the researcher, and 2) student perceptions of the course. Five studies examined course characteristics, two of which also employed mixed methods to collect student perceptions.

Course Characteristics

While Glazier (2016) recognized that personal and circumstantial factors impact the success of individual students, she also hypothesized that the environment itself might lead students to disconnect, perform poorly, and ultimately fail or withdraw from online courses. To test that hypothesis, Glazier designed a teaching experiment, using strategies to build rapport with students in an introductory political science course at a public university. Over a three-year period of time, she taught six sections of the online course with rapport-building measures and three sections without rapport-building features. All other course components—content, activities, assignments, and measures of student assessment—were identical. The rapport-building techniques sought to humanize the instructor (through weekly videos messages), provide student-specific feedback (via handwritten annotations on assignments), and make frequent personal contact with each student (through email). T-test comparisons revealed that students who received rapport-building measures were significantly less likely to withdraw or to receive final course grades of D or F than students who did not receive the measures. The D, F, or Withdrawal rate for students in rapport-building sections was 13.5% lower than for students in non-rapport sections, leading Glazier to conclude that rapport with the online instructor helps students to be more successful. The quantitative findings were reinforced by student surveys and qualitative analysis of student responses to the different course environments. Glazier summarized the implications of these results, stating, "although rapport cannot change students' level of preparedness or the personal life circumstances that may prove challenging in any given semester, rapport just may help students cope with those challenges" (Glazier, 2016, p. 13).

Hegeman (2015) was also interested in the impact of teaching practices in introductory courses. She questioned whether using publisher-generated content as the primary source of instruction diminished teaching presence of the instructor, thereby impacting student success in a college algebra course. To investigate that question, she redesigned the course and compared student outcomes between the two versions. The publisher-centric course included video lectures, animations, completed examples, a guided tutorial for solving homework problems, and one algorithmically generated homework problem that allowed students to demonstrate mastery. To supplement publisher-centric content, the instructor provided typed lecture notes, exam review materials, and video-recordings of handwritten problem solving. In the redesigned instructor-centric course, the instructor delivered 91 video lectures explaining concepts and hand-solving problems. Students were required to complete note-taking sheets—designed to coordinate with the video content—while watching the instructor's video lectures. The publisher textbook and content (the same text used in the original course) became supplemental in the redesigned course. In essence, the primary versus supplementary roles of publisher-generated content and instructor-generated content were reversed. Hegeman (2015) found that students in the instructor-centric course performed significantly better on assessments than students in the publisher-centric course. Moreover, the student pass rate was significantly higher in the course with strategic teaching presence than in the original, publisher-designed course, lending support to the conclusion that instructor presence impacted student achievement.

Similar to Glazier (2016) and Hegeman (2015), Jaggars and Xu (2016) found that interaction between the student and instructor encouraged student commitment and stronger academic performance. Jaggars and Xu (2016) assessed 23 online courses taught at two community colleges based on four characteristics: organization and presentation, learning objectives and assessments, interpersonal interaction, and use of technology. They subsequently compared student outcomes in the courses with results of their design assessment. Jaggars and Xu found the quality of interpersonal interaction within the course was significantly related to student grades. The other three features—while desirable—did not predict student grades. Differences in interaction levels between courses seemed to be strongly led by instructor initiative. Forty-three of the 678 participants in the study were subsequently interviewed. Interviews revealed that students valued interaction with the instructor more highly than interaction with other students.

Based on the emphasis in previous research regarding teaching presence, Olson and McCracken (2014) explored the idea that real-time interaction with students via synchronous lectures might increase student engagement and achievement. Using a quasi-experimental design, Olson and McCracken (2014) devised a case study with two sections of an online course. One section was entirely asynchronous, while the second included a weekly online meeting. The two courses were the same in all other regards. Results showed no significant difference in student achievement measured by grades. Further, student survey responses provided no indication that the synchronous sessions contributed to student learning.

Student Perceptions

Social presence. Two studies found a significant relationship between students' perception of social presence in a course and their final grade for the course. Liu, Gomez, and Yen (2009) investigated perceived social presence among 108 students taking one or more online courses at an urban community college, measuring students' perception of social presence via the Social Presence and Privacy Questionnaire (SPPQ). Although the questions on this assessment could be reliably grouped into five subscales, this study collapsed the scale scores to consider social presence as a single construct. In other words, social presence served as the single independent variable. Liu and colleagues used binary logistic regression to evaluate social presence against the dependent variable of student retention (defined as a final course grade of C or better). Ordinal logistic regression was used to evaluate social presence against the dependent variable of final grade (which included withdrawal and incomplete, as well as letter grades A , B, C, D, and F). Results indicated that the perception of social presence among community college students is positively and significantly related to probabilities of completing an online course with a grade of C or better and positively related to earning a higher course grade.

Rockinson-Szapkiw et al. (2016) measured social presence, teaching presence, and cognitive presence using a Community of Inquiry (CoI) assessment. Additionally, they explored student perceptions of learning using the Cognitive, Affective, and Psychomotor (CAP) Perceived Learning Scale. Their study of 131 graduate students at a private university included gender, ethnicity, and delivery format (asynchronous/synchronous) as control variables. Analysis via hierarchical multiple regression revealed that gender and ethnicity explained 6.9% of variance in final course points. The final model, composed of demographics, teaching presence, social presence, cognitive presence, and perceived cognitive learning, accounted for 55.6% of the variance in course points. Inclusion of course format did not result in a significant change in variance. Higher scores on four of six scales were positively associated with final course grades: teaching presence, social presence, cognitive presence, and perceived cognitive learning. The scale scores for perceived affective learning and psychomotor learning did not show a statistically significant relationship to students' course points.

Student satisfaction. Three studies found an association between student satisfaction with the course and final course outcome (Levy, 2007; Park & Choi, 2009; Wang et al., 2013). By contrast, two studies (Baturay & Yukselturk, 2015; Joo et al., 2013) concluded that satisfaction with the course did not have a statistically significant effect. Joo et al. (2013) did find, however, that perceived relevance of assigned tasks in the course exerted a significant effect on achievement. Park and Choi (2009) also concluded that perceived course relevance had a significant effect on course completion.

Instructor "care." As discussed under course characteristics, both Glazier (2016) and Jaggars and Xu (2016) used qualitative methods to explore student perceptions of interaction in the course. Both reported that student outcomes were positively impacted by belief that the instructor cared about students in the course. Jaggars and Xu (2016) reported that students perceived these actions as an indication of instructor care: posting announcements and reminders, inviting student questions, responding quickly to student queries, and soliciting student feedback.

Significance and Limitations

Ninety-four discreet variables were identified from the 32 studies reviewed. Roughly half the variables proved statistically significant in at least one study; the other half showed no evidence of significance. For many variables, evidence of association with student outcomes in online courses was mixed. Several variables were only found significant in a single study or, in many cases, were only examined in a single study. As a method of weighing the evidence, results were parsed to identify variables found statistically significant in two or more studies. These 17 variables, along with the studies in which they were found significant, are displayed in Table 2.2 in alphabetical order within each subcategory.

Table 2.2 Variables reported statistically significant in two or more studies.

	Personal Variables	
Demographics	Age	Cochran, Campbell, Baker & Leads, 2014; Suphi & Yaratan, 2012
	Gender	Aragon & Johnson, 2008; Cochran et al., 2014; Kupczynski, Brown, Holland, & Uriegas, 2014;Rockinson-Szapkiw, Wendt, Wighting, & Nisbet, 2016; Suphi & Yaratan, 2012
	Race, Ethnicity, Nationality	Cochran et al, 2014; Rockinson-Szapkiw et al., 2016; Suphi & Yaratan, 2012
Acad. Performance	Computer Skills	Harrell & Bower, 2011; Rakap, 2010
	Cumulative GPA	Aragon & Johnson, 2008; Cochran et al., 2014; Hachey, Wladis, & Conway, 2014; Jost, Rude-Parkins, & Githens, 2012; Harrell & Bower, 2011; Suphi & Yaratan, 2012
Non-cognitive Attributes	Learning Styles	Harrell & Bower, 2011; Rakap, 2010
	Locus of Control	Lee, Choi, & Kim, 2013; Rogers, 2015
	Self-Efficacy	Joo, Lim, & Kim, 2013; Wang, Shannon, & Ross, 2013
Student Strategies	Effort Regulation	Puzziferro, 2008; Yukselturk & Bulut, 2007
	Metacognitive Self-Regulation	Lee et al., 2013; Wang et al., 2013; Yukselturk & Bulut, 2007
	Time & Environment Management	Puzziferro, 2008; Wang et al., 2013
	Circumstantial Variables	
Academic Circumstances	Class Standing	Cochran et al., 2014; Levy, 2007
	Prior Online Course Success	Hachey, Wladis, & Conway, 2012; 2014
	Course Variables	
Student Perceptions	Course Relevance	Joo et al., 2013; Park & Choi, 2009
	Instructor "Care"	Glazier, 2016; Jaggars & Xu, 2016
	Satisfaction with Course	Levy, 2007; Park & Choi, 2009; Wang et al., 2013
	Social Presence	Liu, Gomez, & Yen, 2009; Rockinson-Szapkiw et al., 2016

Additional Variables of Interest

Several variables were notably absent in prior studies. Five studies evaluated prior experience in online courses, but none considered whether students were taking online courses exclusively rather than including both online courses and face-to-face courses in their class schedule. Class standing was evaluated in two prior studies, but none of the reviewed studies investigated course level. Class standing and course level are typically associated with one another, but the relationship is not exclusive. Five studies investigated various course characteristics, but none considered class size as a variable. Class size, meaning the number of participants in an online course, could have a substantial impact on the types of interaction that take place.

Stability of Internal Control

Eight of the reviewed studies examined locus of control—a product of Rotter's Social Learning Theory (Otten, 1977; Rotter, 1966). None of the studies examined stability of control.

A student with *internal locus of control* may believe poor grades result from lack of effort or from lack of ability. By contrast, a student with *external locus of control* may believe poor grades result from bad luck or from inadequate instruction (Richardson, Abraham, & Bond, 2012). Weiner (1986) argued that Rotter's construct of internal/external control failed to consider stability of control. A student with internal locus of control might believe grades result from effort (a changeable factor over which he/she has control). But a student with internal locus of control might also believe grades result from ability or aptitude—which many students believe to be stable and unchangeable (internal to self, but beyond their power to change).

Dweck (2013) addressed stability of control by identifying two different mindsets that students might hold about their own intelligence. Students with an *entity theory* believe intelligence to be fixed and concrete. Those with an *incremental theory* believe intelligence to be a dynamic quality that can be increased (Dweck, 2013; Yeager & Dweck, 2012). Dweck found elementary and secondary students' mindsets affect goal choice and effort, thereby predicting achievement. Mindset was not included as a variable in any of the studies reviewed here, despite the fact that it has been shown significant among other populations.

Non-Traditional Student Obligations

Theoretical models emphasize that non-traditional students have other obligations in addition to academic course work. Three studies in this review investigated the variable of employment. One study included marital status and number of children as variables. None of the reviewed studies asked participants whether their extra-curricular obligations included significant time and effort caring for family members.

Alaska-Specific Variables

The purpose of the current study was to increase understanding of the factors that contribute to online success in the context of Alaska. Two variables investigated in the current study are specifically related to this context: beneficiaries of the UA Scholar Program and student location.

Beginning in 1999, the University of Alaska instituted a program dubbed UA Scholars that was designed to keep Alaska's brightest high school students in state for pursuit of higher education. Through this program, the top ten percent of graduating seniors from Alaska high schools receive a $12,000 scholarship to the UA campus of their choice (University of Alaska, n.d.). The university tracks the progress of these students.

Alaska is unique among states in the U.S. for its vast size. Large areas of the state are inaccessible by road. Additionally, many of the off-road areas are challenged by low-bandwidth Internet access. Thus, student location is a salient factor in understanding student success within the state.

Need for the Current Study

It is clear that much is still unknown about student success in online courses. While scholars have researched post-secondary achievement for decades, research related to online learning is relatively new. As evidenced by the sheer number of variables identified in this review, researchers still seem to be in early stages of exploration. Several variables—identified in the previous section—were omitted in prior research. Many variables were evaluated in a single study; results must be replicated to confirm significance. In other cases, variables were explored in multiple studies, but results were contradictory. Some of the disparity in results likely stemmed from the diversity of contexts. For example, two studies in this review pertained to developmental courses and self-paced learning. Several studies evaluated students at the community college level, while other studies addressed graduate students. More research is needed at each of these levels.

Finally, more research is needed to understand the complexity of factors—the interplay between student characteristics and context—that impacts student success.

Theoretical frameworks discussed in this chapter all reflect the belief that retention, persistence, and attrition are multi-faceted. As Rovai asserted, “It is not credible to attribute student attrition to any single student, course, or school characteristic” (2003, p. 12). Yet, many of the studies in this review were limited to a single type of variable—personal, circumstantial, or course factors. Only four of the 32 studies addressed variables from all three areas (Baturay & Yukselturk, 2015; Levy, 2007; Park & Choi, 2009; Wang et al., 2013). The current study adds to the body of evidence by targeting some of these identified gaps.

Chapter 3: Methodology

Alaska's large size and low population density make online education particularly important as a means of increasing student access to higher education. Given concerns in the literature regarding poor success and retention rates in online courses in general (Allen & Seaman, 2013; Berge & Huang, 2004; Layne et al., 2013; Park & Choi, 2009), the current study was undertaken to examine determinants of success in online courses delivered by a public university in Alaska.

Research Design

This research applied a strengths-based perspective and mixed methodologies to develop a multilevel understanding of factors that influence student success. According to Shushok and Hulme (2006), research on retention and success has historically focused on why students leave college rather than examining why they stay, applying a pathology-based model to understanding the issues. Strengths-based education conversely seeks to identify "what is right" with students rather than diagnosing "what is wrong" (Lopez & Louis, 2009; Shushok & Hulme, 2006; Stebleton, Soria, & Albecker, 2012). Maton et al. (2004) contrasted strengths-based research approaches to traditional deficit-based approaches, pointing out that the latter often separate people from the context in which they live. Strengths-based research, on the other hand, promotes an ecological view of the relationship between subjects and their circumstances. This implicit emphasis on context made the strengths-based perspective a natural choice for studying student success in the state of Alaska.

To complement the strengths-based approach, a mixed-method design was selected, incorporating both quantitative and qualitative data collection and analyses.

According to Creswell (2013), early thoughts about the value of mixed methods derived from the notion that all methods have biases and weaknesses. Early proponents of mixed methods believed collecting both quantitative and qualitative data might help to neutralize the inherent weakness of each. Major work in developing and refining the field of mixed-methods research began in the middle to late 1980s and practical issues related to use of the model are widely discussed today (Creswell, 2013). Beyond the value in neutralizing weaknesses, mixed methods may provide deeper insights. The mixed-methods design chosen for this study was explanatory sequential. First, quantitative methods were used to identify correlation between student characteristics or circumstances and success in online courses. As depicted in Figure 3.1, qualitative methods were subsequently employed to explain and elaborate on the elements of their success. Quantitative and qualitative data were combined for final analysis.

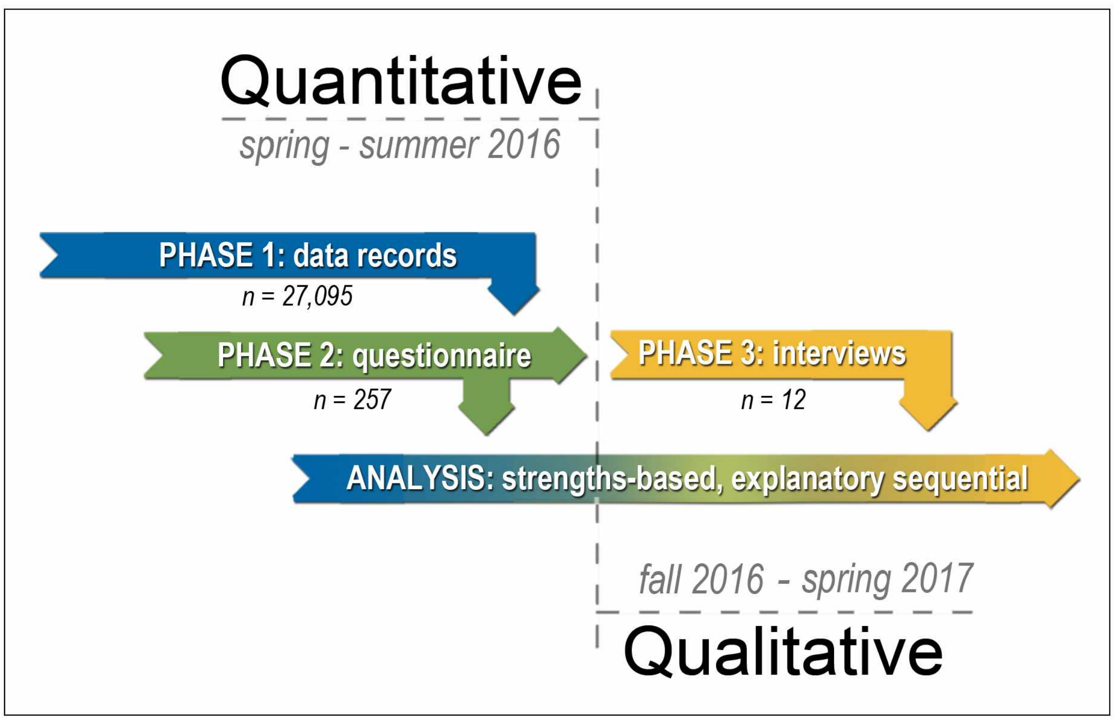

Figure 3.1 Diagram of the research design.

Theoretical Model

Berge and Huang's (2004) model of student retention was selected as the theoretical underpinning for this research based on the flexible nature of their framework and their emphasis on context. As Berge and Huang explained, "Generalizations about retention can be misleading because each institution is dynamically unique in terms of academic emphasis and institutional culture" (2004, p. 21). Berge and Huang categorized student retention factors into three clusters: personal variables, circumstantial variables, and institutional variables. The variables in this study were also organized into three categories, but with a slight modification to the domain of institutional variables. Because the same institution delivered all course enrollments included in this research, there were no differing institutional variables to consider. Instead, course-specific elements were selected as a subset of institutional characteristics. Thus, the three categories included in this study were personal variables, circumstantial variables, and course variables. To further elucidate the distinction between categories, the clusters were envisioned as student identity, student context, and the student's experience in completing the course (Figure 3.2).

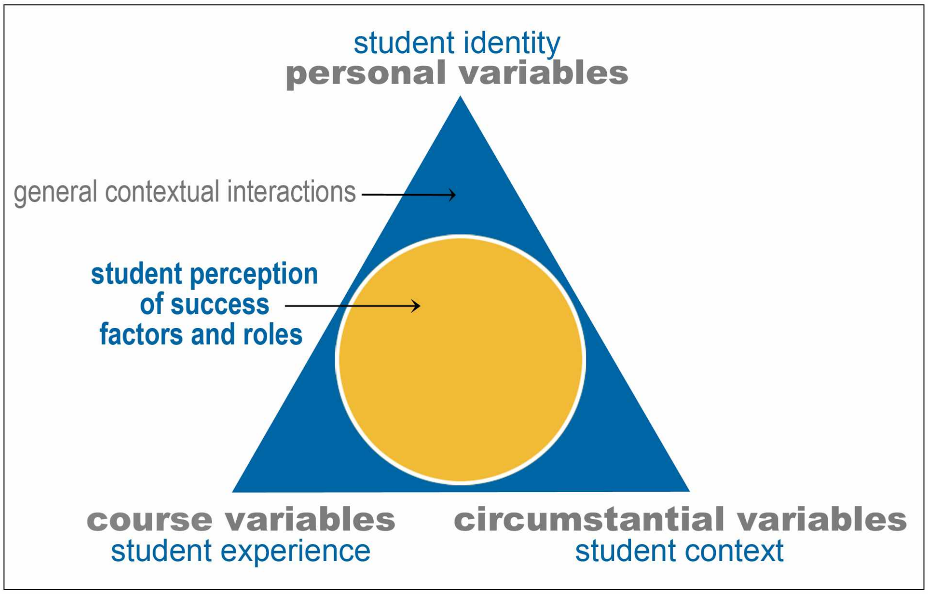

Figure 3.2 Theoretical framework for the study, modified from Berge and Huang (2004).

Research Questions

This study aimed to increase understanding of the factors that predict or contribute to student success in post-secondary online courses delivered by the University of Alaska Fairbanks. The explanatory sequential model included three phases of data collection and analysis: two quantitative phases, followed by qualitative interviews. The two quantitative phases were designed to answer these questions:

1. To what extent do personal variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?
2. To what extent do circumstantial variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?
3. To what extent do course variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?

4. To what extent can a combination of personal, circumstantial, and course variables be used to predict success in asynchronous online courses at the University of Alaska Fairbanks?

Results from the first two phases informed selection of a stratified sample for the third, qualitative phase. Interviews completed during Phase Three addressed these questions:

5. How do successful online students perceive the impact of personal, circumstantial, and course variables in their educational experience?
6. How do successful online students define their role versus the instructor's role, and how does each role contribute to student success?
7. How have successful online students been able to overcome challenges and persist to completion?

Research Site

This research was conducted at the University of Alaska Fairbanks (UAF), a public doctoral university whose primary campus is located in interior Alaska. The research protocol for this study was determined to be exempt by the Institutional Review Board at UAF. Carnegie Classification distinguishes doctoral universities by three levels of research activity: moderate, higher, and highest. UAF is classified as R2—an institution with "higher research activity" (Indiana University Center for Postsecondary Research, 2016). With seven campuses across the state, UAF serves nearly 10,000 students—eighty-eight percent of whom are undergraduates (University of Alaska Fairbanks, 2016). One distinctive characteristic of this institution is its breadth of programs: UAF offers workforce development and vocational programs, as well as Baccalaureate degrees, Masters and PhDs.

This study examined students who took online courses via UAF eLearning. The eLearning unit is responsible for supporting all asynchronous online courses offered through UAF academic departments. More than 25 eLearning staff members provide instructional design, faculty development and support, enrollment management, and student services for online courses. Limiting the study to eLearning-supported courses ensured many aspects of the course design, delivery, and support were consistent—resulting in a more controlled analysis of variables.

Participants

As an overview, the investigation examined a pool of students who took online courses delivered through UAF eLearning over the course of four academic years (Fall 2011 through Spring 2015), as described below. Preliminary analysis at each stage informed selection of participants for the following phase. With each subsequent phase, the list of participants was narrowed to provide tighter focus and allow for additional data to be collected for the focused sample population.

Study Population

The first phase of research included 27,095 records, each defined as a distinct student within a distinct course for a given semester. A conscious decision was made to include a separate record for each unique combination of student-course-semester, based on the fact that many students took multiple online courses during the four-year timespan. For students who took courses over successive years, some personal information remained constant (e.g., gender, race) while other characteristics changed (e.g., age, class standing, cumulative GPA). Because a student might have been successful in some courses but unsuccessful in others, and because some of the student characteristics were subject to change over the time period, it was logical to treat each student-course-semester combination as a distinct case. Additionally, the fact that many students were successful in some courses and unsuccessful in others underscored the importance of evaluating the specific combination of personal, circumstantial, and course variables simultaneously. Of the 27,095 Phase One cases, 68% were female and 32% were male. The racial composition of student enrollments is displayed in Table 3.1.

Table 3.1. Racial composition of Phase One subjects.

	Frequency	Percent
Unknown	7,903	29.2
Asian	579	2.1
Black	826	3.0
Hawaiian/Pacific Islander	183	0.7
Native/Indian	3,739	13.8
White	13,865	51.2
Total	27,095	100.0

Narrowed Sample Frame

Phase Two participants were a subpopulation of Phase One. Whereas the first phase considered online course enrollments over a time span of eight semesters (Fall 2011 through Spring 2015), the second phase honed in on enrollments from a single semester: Spring 2015. The latest semester in the dataset was selected, with the expectation that students might recall details more vividly for the most recent semester. Moreover, the sampling frame for Phase Two became each unique student rather than each student-course combination. In other words, each student was invited to participate once—regardless of how many online courses he/she took during the Spring 2015 semester. Less than half the Phase Two questions were course specific; the majority of questions addressed overarching student beliefs and circumstances. Therefore, asking students in multiple courses to complete the survey multiple times would have been redundant. Three hundred and twenty students who successfully completed an online course during Spring 2015 subsequently completed the Phase Two assessment of non-cognitive factors (described in detail below).

Interview Participants

Using a stratified sample, successful students (i.e., those who earned a final course grade of C- or higher) were selected from among Phase Two participants and invited, via email, to participate in Phase Three interviews. Students who responded to the email invitation were offered several available time slots. After selecting a time and returning the signed consent form, participants were interviewed by telephone or web meeting. In total, twelve students were interviewed.

The remainder of this chapter will describe selection methods in greater detail and further explain the data collection procedures, instruments, and methods of analysis employed at each stage. This information has been organized by phase, reflecting the sequential nature of this study and the order in which data were collected and analyzed.

Phase One

The objective of Phase One was to examine the relationship between online student success and a variety of factors categorized as personal, circumstantial, and course variables. Although there are numerous ways to measure success, in this study success was defined as earning a final course grade of C- or higher. This definition created a binary outcome: students were either successful or non-successful. A final grade of C- or higher is significant in the academic system because it is a *passing grade* that signifies sufficient mastery to move forward in the academic sequence. Thus success, delineated by final grade, became the dependent variable for statistical analysis.

Independent Variables

As previously discussed, data were clustered into three categories: personal, circumstantial, and course variables. Half the independent variables were dichotomous; the others were nominal and ordinal. Three variables that might have been configured to be continuous were grouped to become ordinal. Age and cumulative GPA were grouped in the original extraction from the student information system; class size was later grouped to become ordinal. Location remained nominal, but was grouped into five categories, as described below. Complete lists of values for Phase One and Phase Two variables are included among the descriptive statistics in Chapter Four (Tables 4.1, 4.2, and 4.3). The summary presented in Table 3.2 outlines the classification of Phase One variables by cluster (personal, circumstantial, course) and by measurement level (dichotomous, nominal, ordinal).

Table 3.2. Phase One independent variables. Symbols indicate level of measurement.

Personal Variables	Circumstantial Variables	Course Variables
◐ Gender	◐ First-time eLearning Student	Course Level
◐ UA Scholar	◐ eLearning Courses Only	Class Size
◐ International Student	◐ Full-time Student	
◐ Active Military	● Degree Level	
◐ UA Athlete	● Financial Aid	Key:
● Race	● Location	◐ = dichotomous
Age	● Class Standing	● = nominal
Cumulative GPA		= ordinal

Location variable. Location was derived from the mailing address listed in the student information system. Raw location data included twenty-five countries and all fifty states. Because the emphasis of the study was the unique context of Alaska, students outside the state, whether from another country or another state, were all grouped into a single category. These cases, labeled *outside Alaska,* accounted for nine percent of total enrollments. Students within Alaska were distributed across more than 200 locations, depicted in Figure 3.3.

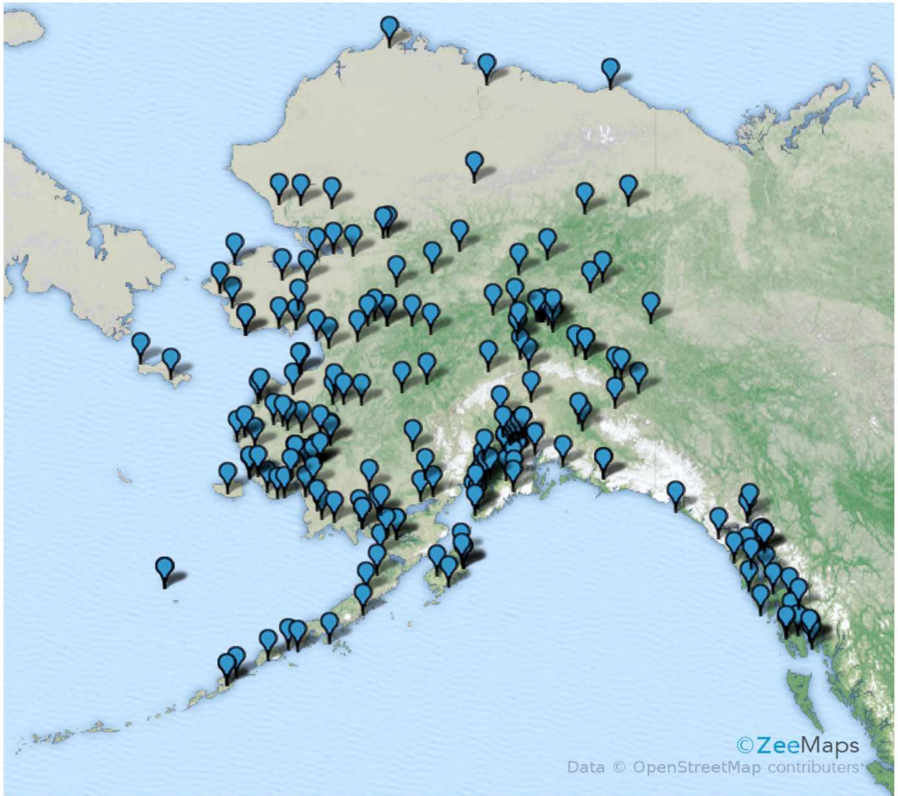

Figure 3.3 Student locations within Alaska. Map was created with ZeeMaps and used by permission.

Much of Alaska is inaccessible by road. Travel to these areas requires another means of transportation, such as plane or boat. Typically, the regions without road access also have limited access to Internet service. Many rural residents do not have Internet in their homes; those who do are often challenged by low bandwidth. Because size of the community combined with geographic location play a role in the availability of local Internet service, those factors were used as proxies for dividing locations within the state into four categories:

1. *Alaska Urban* included the three major cities of Anchorage, Fairbanks, and Juneau.

2. *Alaska Suburban* included fourteen locations near Anchorage and Fairbanks. Locations in this category were located on the road system, with access to high-bandwidth Internet service.
3. *Alaska City* was defined as an incorporated city with a population of 1,500 or greater as identified by the 2010 census (excluding those categorized as urban or suburban). Road and Internet access varied for locations in this category.
4. *Alaska Rural* was defined as a community for which the 2010 census reported less than 1,500 residents. The locations in this category were typically off the road system and generally had limited options for Internet access.

The distribution of Phase One cases (unique combinations of student-course-semester) is displayed by location in Table 3.3.

Table 3.3. Location of Phase One cases.

	Frequency	Percent
AK Urban	14,910	55.0
AK Suburban	4,790	17.7
AK City	2,633	9.7
AK Rural	2,188	8.1
Outside AK	2,559	9.4
Missing/unknown	15	0.1
Total	27,095	100.0

Collection

Data were collected for eight semesters: Fall 2011, Spring 2012, Fall 2012, Spring 2013, Fall 2013, Spring 2014, Fall 2014, and Spring 2015. Summer enrollments were excluded from the study, under the assumption that students who enrolled in summer courses might have somewhat different characteristics than those who enrolled during traditional academic semesters of fall and spring. UAF Planning, Analysis, and Institutional Research (PAIR) provided the dataset for Phase One as an extract from the university's student information system.

Analyses

Logistic regression was used to examine the relationship between seventeen possible predictors and one outcome variable (success), using existing data from the University of Alaska student information system. The general model used was:

$$\text{Logit}(\hat{Y}) = b_0 + b_1X_{1\ldots}\ b_{17}X_{17} \tag{3.1}$$

Where $\hat{Y}$ is success, X_1 is gender, X_2 is UA Scholar, X_3 is international student, X_4 is active military, X_5 is UA athlete, X_6 is race, X_7 is age, X_8 is cumulative grade point average, X_9 is first-time eLearning student, X_{10} is eLearning courses only, X_{11} is full-time student, X_{12} is degree level, X_{13} is financial aid, X_{14} is location, X_{15} is class standing, X_{16} is course level, and X_{17} is class size, as described in Table 3.2.

Framing of the research questions, as well as the chosen levels of measurement, impacted the types of analyses deemed appropriate. This study might have been designed to analyze the difference between successful students versus non-successful students. Instead, the research questions were framed to answer *associational questions* about the degree to which various factors contributed to success. The two most suitable options for analyzing a complex associational research question with a dichotomous dependent variable are logistic regression and discriminant analysis. According to Gliner, Morgan, and Leech (2009) discriminant analysis is more appropriate in cases where the independent variables are all normally distributed and logistic regression is a better choice when some or all of the independent variables are dichotomous. As previously noted, half the Phase One variables were dichotomous; therefore, logistic regression was the preferred method.

Although a correlational study could have been completed between success and each of the seventeen variables independently, this would have been an oversimplification prone to unsatisfactory answers. As revealed in the literature, prior studies often focused on single variables. By contrast, fewer studies have examined the integral contribution of multiple variables in combination (Berge & Huang, 2004; Herbert, 2006; Joo et al., 2011).

Phase Two

Phase Two continued quantitative data collection among students in asynchronous online courses at UAF regarding factors related to their success in these courses. Adding to variables retrieved from the student information system in Phase One, Phase Two queried a subset of Phase One subjects for additional information, using perspectives drawn from psychology, sociology, and education. More than 2,500 students from Spring 2015 were invited to complete a questionnaire designed to measure non-cognitive motivational factors and student perceptions. The Phase Two instrument also collected three personal/circumstantial variables not available from the university's student information system. A coding system was used to match Phase Two responses with each subject's Phase One data, so that variables from the two phases could be examined together. The outcome variable pertaining to grade was refined in Phase Two. While the outcome variable for Phase One was a binary measure of success/non-success, the outcome variable for Phase Two became final course grade, measured at an ordinal level. Rationale for this decision will be discussed in subsequent sections.

Objectives

Objectives of this second quantitative phase were to:

1. Examine the relationship between success of online students and the psychological constructs of academic locus of control, self-efficacy, and mindset.
2. Examine the relationship between success of online students and the psychosocial construct of perceived social support.
3. Examine the relationship between success of online students and the course characteristics of social presence and teaching presence.
4. Examine the relationship between success of online students and three circumstantial variables: whether either parent graduated from college, full- or part-time student employment, and whether the student had responsibilities of caring for family members.
5. Explore relationships between the combination of 28 independent variables collected in Phases One and Two against the outcome variable of final course grade.

Independent Variables

Table 3.4 presents the independent variables collected in Phase Two. The table is organized by classification within the underlying framework of personal, circumstantial, and course variables. Most independent variables in Phase Two were analyzed as dichotomous values. Each question in the instrument that related to a psychological, psychosocial, or educational construct was first measured at an ordinal level (e.g., Likert score of one-to-five). Each scale score for each participant was then calculated as the mean of constituent question scores. Finally, each scale score for each participant was categorized with a binary value of high/low due to the non-parametric distribution of responses.

Table 3.4 Phase Two independent variables.

Personal Variables	Circumstantial Variables	Course Variables
◐ High Perceived Academic Control	◐ Parent was College Graduate	◐ High Teaching Presence
◐ High Self-efficacy	● Employed Full- or Part-time	◐ High Social Presence
◐ High Incremental Theory Mindset	◐ Significant Time/Effort Caring for Family	Key:
	◐ High Perceived Social Support of a Special Person	◐ = dichotomous ● = nominal
	◐ High Perceived Social Support of Family	
	◐ High Perceived Social Support of Friends	

Instrument

Student beliefs and perceptions situated within the constructs of this study have all been researched individually in earlier studies. Rather than starting anew, Phase Two began by selecting previously validated instruments and combining them into a single instrument. After a careful review of the literature, the six scales below were selected for inclusion in the Phase Two questionnaire. Permission was secured for the use of each of these instruments. Copies of the permissions are included in the Appendices of this document.

Locus of control. Halpert and Hill (2011) assembled 28 commonly used locus of control scales derived from Julian Rotter's 1966 work, including derivations that targeted specific groups and ages. Three previously constructed scales created for the specific context of academic performance among college students were considered for this research: 1) Academic Locus of Control (ALOC) originally developed by Trice (1985) and revised by Curtis and Trice (2013); 2) ALOC as adapted by Levy (2007); and 3) Perceived Academic Control (PAC) developed by Perry, Hladkyj, Pekrun, and Pelletier (2001). The revised Trice ALOC was too lengthy for the current study. The Levy ALOC was more concise, but included items that might have been confounded with the construct of mindset. Therefore, the PAC scale was selected for use in this research.

The questionnaire for assessing PAC was comprised of eight items, with half of the items worded positively and half worded negatively. Responses for negatively worded items were reverse scored. The initial study (Perry et al., 2001) showed good internal reliability (Cronbach's $\alpha = .80$). For the current study, one question was edited slightly to conform to common grammar usage in the United States.

Self-efficacy. The General Self-Efficacy Scale (Schwarzer & Jerusalem, 2009) was comprised of ten items. This scale fit well with other scales used for Phase Two, both in the way questions were worded and the Likert scale used for scoring. However, it was truly general—not specific to academic situations. For use in this study, questions were reworded to provide an academic focus.

Mindset. The mindset section of the Phase Two questionnaire used the Theories of Intelligence Scale—Self Form for Adults (Dweck, 2013). Carol Dweck pioneered the work on implicit theories; her scale was the logical choice to include in this study. Dweck's scale included eight items, half of which aligned with entity theory and half of which aligned with an incremental theory of intelligence.

Perceived social support. Zimet, Dahlem, Zimet, and Farley (1988) developed the Multidimensional Scale of Perceived Social Support (MSPSS) as a brief and simple alternative to previously devised instruments. It included twelve questions, with subscales to subjectively assess perceived support from three specific sources: family, friends, and special person (significant other). The MSPSS was first used with a relatively homogenous sample of college students from Duke University. Evaluation of the scale was extended through a study that included pregnant women, adolescents in Europe, and pediatric residents (Zimet, Powell, Farley, Werkman, & Berkoff, 1990). Subsequent research used the MSPSS with a diverse group of students at an urban college (Dahlem, Zimet, & Walker, 1991), psychiatric outpatients (Clara, Cox, Enns, Murray, & Torgrudc, 2003), and two colleges in China (Zhou, Zhu, Zhang, & Cai, 2013), with good evidence of high reliability in those populations as well.

Teaching presence and social presence. Community of Inquiry (CoI) is a social-constructivist process model designed to explain the experience of online learning (Garrison, Anderson, & Archer, 2000). The full CoI model includes three dimensions: social presence, teaching presence, and cognitive presence (Garrison et al., 2000). This study measured students' perception of two CoI elements: social presence and teaching presence. It could be argued that cognitive presence represents a student's perception of his/her own learning. Because the current study uses final course grade as an objective measure of student learning, questions related to cognitive presence were not included.

For several years following initial publication of the CoI model, it was examined primarily via qualitative studies that analyzed transcripts of class discussion forums. Arbaugh and colleagues attempted to advance the model by moving from a descriptive to an inferential approach (Arbaugh et al., 2008). To that end, Arbaugh (2007) developed an instrument to measure students' perception of the three presences. The original instrument was refined and validated by subsequent studies (Arbaugh et al., 2008; Bangert, 2009; Boston et al., 2014; Garrison, Cleveland-Innes, & Fung, 2010; Shea & Bidjerano, 2009; Shea & Bidjerano, 2010). The teaching presence portion of Arbaugh et al.'s (2008) assessment contained thirteen questions; the social presence section included nine questions.

Psychometrics

Unquestionably, it is critical to test data collection instruments before using them. Beliefs and perceptions, the subjects addressed in Phase Two of this study, are arguably more difficult to measure than demographic variables such as age and race. The psychometric principles of validity and reliability provided a means for evaluating the accuracy of the assessment tool and thereby afford increased confidence in veracity of the data (Litwin, 2003).

Although the scales described above were all examined in prior research, with evidence of high validity and strong reliability, they had not previously been compiled into a single instrument. A practical question arose when combining these scales: whether to keep the questions grouped (i.e., locus of control questions grouped together, self-efficacy questions grouped together, etc.) or whether to mix the questions randomly. A second, related question was whether to use the scale values from the original instruments or modify the values to be the same throughout the Phase Two questionnaire. For example, Theories of Intelligence, in its original form, used a scale system of one for strongly agree to six for strongly disagree. Perceived Academic Control, on the other hand, used a scale of one for strongly disagree to five for strongly agree. Not only were the number of options different in these two examples (one-to-six versus one-to-five), but the descriptions were reversed as well (one for strongly agree versus one for strongly disagree). To address these questions, a pilot study was devised to test whether question order and scale size mattered. Two versions of the instrument were developed: Version A clustered the questions by construct and retained the original scale numbers; Version B randomized the questions and adjusted the scales to be consistent, with one for strongly disagree and five for strongly agree.

Both versions of the instrument were created using Google Forms—a choice which had several advantages. First, UAF uses Google Apps as an enterprise solution; it has been sanctioned by the university as a secure solution. Second, gmail is the default email system for students taking UAF eLearning courses, so invitations to participate in the pilot were sent out through this email system. Further, Google Forms, as part of the Google Suite of Apps at UAF, can be used free of charge. Finally, all students invited to participate in the study already had secure login credentials for this system. Therefore, participants did not need to create new accounts and each participant's identity was automatically recorded with their responses.

Pilot. The pilot was conducted in January 2016 to compare results of Version A against Version B of the online form. The sampling frame for the pilot consisted of students who completed an online course through UAF eLearning in Fall 2014. The total number of enrollments was 3,845. Five hundred students from that population were randomly selected and then randomly assigned to either Form A or Form B of the questionnaire.

By means of email, 250 students were invited to complete the Form A questionnaire and 250 students were invited to complete the Form B questionnaire. The email stated that one participant who completed the entire form would be randomly selected to receive a $250 gift card. A follow-up email was sent to members of the sample who did not respond within the first ten days. After two weeks, at the close of data collection, the total response rate was 14%, with 39 responses to Form A and 31 responses to Form B.

An analysis of Cronbach's Alpha for each of the scales in Form A and each of the scales in Form B revealed good internal consistency, with alpha scores ranging from 0.82 to 0.98. When compared against each other, both versions of the questionnaire produced similar reliability scores on all scales, as shown in Table 3.5.

Table 3.5 Comparison of Cronbach's Alpha scores for two versions of questionnaire.

	Form A	Form B
Perceived Academic Control	.820	.827
Mindset	.967	.958
Self-Efficacy	.927	.900
Multidimensional Scale of Perceived Social Support	.926	.918
Teaching Presence	.980	.984
Social Presence	.911	.910

The results of the pilot demonstrated the viability of using a single questionnaire to measure six constructs identified for this study. Further, the use of randomized questions and consistent scale values were not shown to impact reliability. Therefore, the study proceeded using Version B, in which the questions were randomized and scale values were consistent, under the beliefs that: 1) randomization would help the questions seem less repetitive and 2) consistent response options would help reduce the potential for confusion.

Focused Selection of Participants

As previously described, the sampling frame for Phase Two was a subset of the Phase One population. Eight semesters of data were analyzed during Phase One while only one semester—Spring 2015—was evaluated in Phase Two. Moreover, Phase One variables had been measured in real time in each of eight semesters by the university's student information system. Each unique combination of student-course-semester was retained for examination in Phase One. By contrast, the variables for Phase Two were collected at a single point in time by a questionnaire designed to measure student motivation and perception. As such, it was determined that asking students to take the assessment more than once would be redundant. Therefore, students who took more than one eLearning course during Spring 2015 were identified, so that a single invitation to participate might be extended.

Excluding a small number of students under the age of 18 (as specified in the research protocol) yielded 2,665 unique students enrolled in UAF eLearning courses in Spring 2015. Roughly 60 percent took a single eLearning course, while 40 percent took two or more eLearning courses that semester. For those who took multiple courses, only one course enrollment was retained for the study; in these cases, the course to be used was chosen by random selection. Forty-three students who had completed the pilot were eliminated from the study to rule out issues of practice effects; one student was removed by request; and 40 others were removed due to inconclusive final grades (incompletes, audits, and non-credit-bearing professional courses). In this second phase of the study, the dependent variable of final course grade was measured at an ordinal level.

Data Collection

From the resulting dataset an email invitation was sent to 2,581 potential participants. As incentive for participation, students who completed the questionnaire were entered into a random drawing for airline miles. The assessment was available for three weeks, with one reminder sent midway. The email invitation included a unique access code specific to the course and student. For students who took more than one course, the invitation specifically indicated which course was being included in the study. Participants were asked to enter their student identification number, the unique access code, and the course they took; the combination of their answers to these three questions served to verify their identity and to ensure their answers about teaching presence and social presence related to the correct course variables. A total of 320 students submitted the questionnaire, but seventeen responses showed a discrepancy between the access code and the reported course. The seventeen responses with this type of incongruity were removed, leaving 303 cases for analysis.

Preparation for Analysis

Exploratory factor analysis (EFA) was used to examine scale structure and the relationship between variables collected in Phase Two. As previously described, the Phase Two instrument included sixty questions drawn from six distinct— previously validated—scales. Before commencing exploratory factor analysis, suitability of the data was evaluated based on sample size and strength of the relationships among variables.

The literature revealed diverse opinions with regard to optimum sample size for factor analysis. Recommendations generally fell into one of two categories: 1) minimum number of cases or 2) subject-to-variable ratio. Recommended minimums for an adequate number of cases ranged from 50 to 1000; recommendations for ratios ranged from 3:1 to 20:1 (Williams, Onsman, & Brown, 2010). Tabachnick and Fidell's (2007) text was referenced in multiple studies, suggesting 300 cases as a comforting minimum. According to Beavers et al. (2013) there is emerging belief, however, that neither ratios nor case numbers should be trusted as generalized guidelines. Rather, the adequacy of a sample depends upon strength of the factor loadings; weaker loadings require a larger sample size to instill confidence in the results.

As a baseline, the current sample size met Tabachnick and Fidell's (2007) general recommendation (more than 300 cases) and Suhr's (2006) criteria for subject-to-item ratio of 5-to-1, lending support for the decision to proceed. Moderate-to-high factor loadings later confirmed adequacy of the sample size.

Factor Analysis

By means of exploratory factor analysis, eight scales were identified from the Phase Two questionnaire responses. The derived scales aligned well with the constructs originally proposed for investigation. A mean score was calculated for each participant on each of the scales. Visual examination of the histogram for each scale—using each participant's mean score—revealed that responses on all eight scales were skewed to the right. As a result, non-parametric techniques were used on all subsequent analyses, because non-parametric tests are not based on an assumption of normal distribution (Pallant, 2013). Dichotomous bins were then created for each student's score on each scale. Mean scale scores of 4.0 to 5.0 were categorized as "high" while scores below 4.0 were "not high."

Response Bias

Evaluation of the data revealed a disproportionate number of responses from students categorized as *successful*, with a final course grade of C- or higher. While the success rate for the total population of Spring 2015 was 75.5%, the success rate among respondents to the Phase Two questionnaire was 87%. Such a low rate of return from the non-success group (only 41 out of 303 participants) limited the likelihood of drawing statistically significant conclusions about students who did not complete their online course successfully. Therefore, the research design was refined to examine successful students only, and to evaluate their success at the ordinal level of final course grade rather than binary measure of success/non-success. Five participants were subsequently removed who had received a "P" grade. Analyses for Phase Two proceeded with the 257 respondents who earned final course grades of C- to A+. From the outset, this study was designed to be a strengths-based investigation; adjusting Phase Two to include only successful responses was a congruent decision that aligned with the overarching research questions and intent of the investigation.

Analyses

Crosstabs were used to assess the distribution of Phase Two variables across final grade categories. High scale scores with a statistically significant correlation to final grade were subsequently assessed by means of Mann-Whitney U tests.

Phase Three

The objective of Phase Three was to explicate more fully the elements of student success in online courses. Data were collected via individual interviews, providing an opportunity for successful students to discuss and elaborate on factors pertaining to their success.

A pilot was conducted during Spring semester 2014 to inform question development for the Phase Three interview protocol and to explore effective processes for conducting interviews via the Internet. The pilot used purposive sampling to identify a pool of fifty participants who successfully completed ENGL F200X through UAF eLearning & Distance Education during Fall semester 2013, earning a final grade of C- or higher. All 50 students were invited, via email, to participate in individual interviews; the first three to respond were selected. Two interviews were conducted using Blackboard

Collaborate; one interview was conducted via Skype. Each interview was transcribed and coded. Through the process of open and then axial coding, the contrast between student roles and instructor roles emerged as a primary theme. As a result, the language of "roles" was prominently incorporated into the interview questions for Phase Three. The semi-structured interview protocol is included as an appendix to this document.

Interview Protocol

Candidates for Phase Three were identified from the list of successful students in Spring 2015 who completed the Phase Two questionnaire. Because Phase Two analyses revealed distinctions by class standing, a stratified sample was drawn for Phase Three that included two students from each class standing: non-degree, first-time freshmen, continuing freshmen (not first time), sophomores, juniors, seniors, and graduate students. Participants selected by means of this sampling procedure were invited via email to schedule an online or phone interview with the researcher. The population of first-time freshmen for Spring 2015 was very small, because first-time freshmen usually begin during fall semester rather than spring. Only three first-time freshmen completed the Phase Two questionnaire; all three were invited to interview, but none responded. Interviews for selected participants in other class standings were conducted individually via Internet and/or phone at a time amenable to each participant. Interviews were recorded and transcribed prior to coding.

Analysis

NVivo qualitative data analysis software supported a two-stage process of analysis. During the first cycle, aligned with methods described by Saldaña (2009), provisional coding was used to highlight sections of interview transcripts related to quantitative variables in the first two phases. Provisional coding was congruent with the explanatory sequential research design, creating a natural transition between quantitative and qualitative phases of research. Furthermore, it formed the foundation for holistic, combined analysis of data from all three phases.

Upon completion of provisional coding, elaborative coding was used to corroborate the theoretical framework of personal, circumstantial, and institutional variables, and to expand on the concept of student roles versus instructor roles that emerged from the Phase Three pilot. Elaborative coding enabled identification of additional themes and offered an opportunity to capture illustrative phrases in the participants' own words—a concept central to the strengths-based research design.

Comprehensive Analysis

At the conclusion of qualitative analysis, results from all three phases were considered comprehensively. Student comments about their online course experiences provided additional detail consistent with results obtained during quantitative analyses. Through the use of mixed-methods, explanatory sequential design, this study identified characteristics of successful students and then further explicated desirable antecedents, circumstances, and attitudes or habits of successful students.

Chapter 4: Results

Student enrollment in online courses continues to increase each year, despite stakeholders' concerns over the number of online students who do not complete online courses (Allen & Seaman, 2013). Previous research produced inconclusive and often contradictory results regarding specific factors that contribute to (or inhibit) student success in the online environment. The conflicting nature of the evidence may be partially attributable to the diversity of contexts in which the problem of attrition was investigated; context is integral to a complete understanding of student success. Theoretical models of attrition, retention, and persistence posit interplay between characteristics of the student, environment, and institution—with varying levels of emphasis on which factors are most critical. Yet, all models recognize that academic achievement cannot be predicted by a single variable or even a single category of variables (Berge & Huang, 2004; Rovai, 2003).

The purpose of this mixed-method, strengths-based research was to develop a multilevel understanding of factors that influence online student success within the context of Alaska, by evaluating personal, circumstantial, and course variables simultaneously. Data were collected and analyzed sequentially in three phases: two phases of quantitative collection and analysis, followed by qualitative interviews and, finally, comprehensive analysis.

Research Questions

In two quantitative phases, descriptive statistics, logistic regression, exploratory factor analysis, cross-tabulation, chi-square tests for association, and Mann-Whitney U tests were used to answer these questions:

1. To what extent do personal variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?
2. To what extent do circumstantial variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?
3. To what extent do course variables account for student success in asynchronous online courses at the University of Alaska Fairbanks?
4. To what extent can a combination of personal, circumstantial, and course variables be used to predict success in asynchronous online courses at the University of Alaska Fairbanks?

Results from the first two phases informed selection of a stratified random sample of successful students, including two interview participants from each of these groups: non-degree-seeking students, freshmen, sophomores, juniors, seniors, and graduate students. Phase Three interviews were analyzed by provisional and elaborative coding to answer these questions:

5. How do successful online students perceive the impact of personal, circumstantial, and course variables in their educational experience?
6. How do successful online students define their role versus the instructor's role and how does each role contribute to student success?

7. How have successful online students been able to overcome challenges and persist to completion?

At the conclusion of all three phases, results were considered comprehensively to form a strengths-based, contextually informed understanding of online student success in the state of Alaska. Because this study proceeded sequentially, with the results at each stage informing further analysis, results in this chapter are likewise presented in stages: Phase One results, Phase Two results, combined quantitative results, Phase Three results and finally, comprehensive results.

Participants in the study were students who enrolled in an online course supported by UAF eLearning during fall or spring semesters between fall 2011 and spring 2015. Results from Phase One and Phase Two are reported only in aggregate form, thus maintaining participants' confidentiality. Results of Phase Three qualitative interviews use pseudonyms to protect participants' identities. With each phase, the pool of participants narrowed: Phase Three participants were a subset of Phase Two, which in turn was a subset of Phase One. Tables 4.1, 4.2, and 4.3 provide descriptive statistics of participants in the first two phases, organized by personal, circumstantial, and course categories. Descriptive information for participants in the third phase is included in the narrative of results.

Table 4.1 Descriptive statistics for personal variables.

Variable	Phase One n	Phase One %	Phase Two n	Phase Two %
Gender				
Female	18,334	67.7	179	69.6
Male	8,761	32.3	78	30.4
UA Scholar				
Yes	1,983	7.3	33	12.8
No	25,112	92.7	224	87.2
International Student				
Yes	405	1.5	7	2.7
No	26,690	98.5	250	97.3
Active Military				
Yes	4,285	15.8	25	9.7
No	22.810	84.2	232	90.3
UA Athlete				
Yes	899	3.3	7	2.7
No	26,196	96.7	250	97.3
Race				
Unknown	7,903	29.2	66	25.7
Asian	579	2.1	5	1.9
Black	826	3.0	4	1.6
Hawaiian/Pac Island	183	0.7	2	0.8
Native/Indian	3,739	13.8	28	10.9
White	13,865	51.2	152	59.1
Age				
Under 20	3,378	12.5	40	15.6
20–24	9,586	35.4	89	34.6
25–29	5,010	18.5	50	19.5
30–39	5,509	20.3	42	16.3
40–49	2,324	8.6	22	8.6
50 and over	1,288	4.8	14	5.4
Cumulative GPA				
Missing	515	1.9	9	3.5
0.00 to 0.99	911	3.4	1	0.4
1.00 to 1.99	1,643	6.1	3	1.2
2.00 to 2.99	9.075	33.5	49	19.1
3.00 to 3.99	13,340	49.2	169	65.8
4	1,611	5.9	26	10.1
High Perceived Academic Control				
Yes			221	86.0
No			36	14.0
High Incremental Theory Mindset				
Yes			116	45.1
No			141	54.9
High Self-Efficacy				
Yes			174	67.7
No			83	32.2
n =	27,095		257	

Table 4.2 Descriptive statistics for circumstantial variables.

Variable	Phase One n	Phase One %	Phase Two n	Phase Two %
First-time eLearning Student				
Yes	9,885	36.5	78	30.4
No	17,210	63.5	179	69.6
eLearning Courses Only				
Yes	10,246	37.8	65	25.3
No	16,849	62.2	192	74.7
Full-time Student				
Yes	14,341	52.9	146	56.8
No	12,754	47.1	111	43.2
Degree Level				
Non-degree-seeking	2,728	10.1	22	8.6
Occupational Endorsement	125	0.5	1	0.4
Certificate	1,369	5.1	7	2.7
Associate	6,496	24.0	35	13.6
Bachelors	15,345	56.6	158	61.5
Post-bac/Licensure	154	0.6	2	0.8
Masters	800	3.0	29	11.3
Ph.D.	78	0.3	3	1.2
Financial Aid				
No Aid	13,081	48.3	105	40.9
Need-based Aid	7,867	29.0	61	23.7
Non-need-based Aid	6,147	22.7	91	35.4
Location				
AK Urban	14,910	55.0	159	61.9
AK Suburban	4,790	17.7	40	15.6
AK City	2,633	9.7	23	8.9
AK Rural	2,188	8.1	20	7.8
Outside AK	2,559	9.4	15	5.8
Missing/unknown	15	0.1	0	0.0
Class Standing				
Non-degree-seeking	2,728	10.1	22	8.6
First-time Freshman	1,080	4.0	3	1.2
Freshman, Not First-time	4,197	15.5	26	10.1
Sophomore	5,306	19.6	47	18.3
Junior	5,251	19.4	51	19.8
Senior	7,504	27.7	74	28.8
Graduate Student	1,029	3.8	34	13.2
Parent was College Graduate				
Yes			140	54.5
No			117	45.5
Employment				
Full-time			119	46.3
Part-time			92	35.8
Not employed			46	17.8
Significant Time/Effort Caring for Family				
Yes			99	38.5
No			158	61.5
High Perceived Support of Special Person				
Yes			200	77.8
No			57	22.2
High Perceived Support of Family				
Yes			149	58.0
No			108	42.0
High Perceived Support of Friends				
Yes			142	55.3
No			115	44.7
n =	27,095		257	

Table 4.3 Descriptive statistics for course variables.

Variable	Phase One n	Phase One %	Phase Two n	Phase Two %
Course Level				
Developmental	414	1.5	1	0.4
Lower	19,002	70.1	152	59.1
Upper	6,413	23.7	63	24.5
Professional	139	0.5	0	0.0
Graduate Student	1,127	4.2	41	16.0
Class Size				
Less than 15	3,897	14.4	48	18.7
15–30	11,636	42.9	107	41.6
31–45	7,356	27.1	66	25.7
46–60	2,501	9.2	21	8.2
More than 60	1,705	6.3	15	5.8
High Teaching Presence				
Yes			137	53.3
No			120	46.7
High Social Presence				
Yes			83	32.3
No			174	67.7
n =	27,095		257	

Phase One Results

Phase One analyzed 27,095 cases, each defined as a distinct student within a distinct course for a given semester. For participants enrolled in more than one course during this timeframe, each enrollment was analyzed as a separate case. The dichotomous criterion variable was student success, defined as a final course grade of C- or higher. Seventeen predictor variables, grouped within three categories, were assessed by means of descriptive statistics, crosstabs, chi-square tests for association, and logistic regression. A significance level of 0.05 was used in all statistical tests. Data analyses were performed using SPSS, version 22.

Cross-Tabulation and Chi-Square

Cross-tabulations were performed to examine the relationship between student success and each of the variables collected in Phase One. Aligned with the framework of this study, results are presented by category: personal, circumstantial, and course variables.

Personal variables. Chi-square tests for independence were run in conjunction with the cross-tabulations to evaluate significance of the relationship between variables in the contingency tables. Results are summarized in Table 4.4. Significant associations were found between student success and each of the independent variables except active military status. However, Ellis and Steyn (2003) note, "statistical significance does not necessarily imply that the result is important in practice" (p. 51), because large datasets tend to yield small p-values. To evaluate the practical importance of each relationship, the phi coefficient was calculated for 2x2 contingency tables. Cohen's (1988) criteria is widely accepted as a point of reference for effect sizes: 0.10 represents a small effect, 0.30 a medium effect, and 0.50 a large effect. Cumulative GPA approached a large effect size in this analysis, with phi of 0.472. Race showed a small effect size (phi = 0.109). All other effect sizes among Phase One personal variables were negligible.

Table 4.4 Chi-square and phi among Phase One personal variables

	Pearson Chi-Square	df	Asymp. Sig. (2-sided)	Phi
Gender	37.583	1	.000 *	0.037
UA Scholar	53.322	1	.000 *	0.044
International Student	78.683	1	.000 *	0.054
Active Military	.815	1	.367	0.005
UA Athlete	141.421	1	.000 *	0.072
Race	323.448	5	.000 *	0.109
Age	65.825	5	.000 *	0.049
Cum GPA	5909.549	4	.000 *	0.472

* significant at the $p < .001$ level

Circumstantial variables. Crosstabs with chi-square and phi coefficients were used to evaluate relationships between student success and seven circumstantial variables (first-time eLearning student, eLearning courses only, full-time student, degree level, financial aid, location, and class standing). Results are summarized in Table 4.5. Chi-square showed all seven variables to be statistically significant ($p < .001$), but effect sizes for five of the seven variables were negligible. Two variables revealed a small effect size: degree level (phi = 0.113) and class standing (phi = 0.148).

Table 4.5 Chi-square and phi among Phase One circumstantial variables.

	Pearson Chi-Square	df	Asymp. Sig. (2-sided)	Phi
First-time eLearning	44.853	1	.000 *	0.041
eLearning Courses Only	113.809	1	.000 *	0.065
Full-time Student	84.777	1	.000 *	0.056
Degree Level	342.947	7	.000 *	0.113
Financial Aid	111.451	2	.000 *	0.064
Location	72.856	4	.000 *	0.052
Class Standing	595.660	6	.000 *	0.148

* significant at the $p < .001$ level

Course variables. Only two course variables were included in the Phase One investigation: course level and class size. Again, crosstabs with chi-square and phi coefficients were used to evaluate relationships between these variables and the dependent variable of student success. The summary of results is presented in Table 4.6. Course level was statistically significant with a small effect size ($p < .001$, phi = 0.135). Class size was statistically significant, but not practically significant ($p < .01$, phi = 0.025).

Table 4.6 Chi-square and phi among Phase One course variables.

	Pearson Chi-Square	df	Asymp. Sig. (2-sided)	Phi
Course Level	494.101	4	.000 *	0.135
Class Size	16.314	4	.003 **	0.025

* significant at the $p < .001$ level

** significant at the $p < .01$ level

Logistic Regression

Binomial logistic regression was used to evaluate whether specific variables—or a combination of variables—could predict the outcome of success among online students. Results revealed cumulative GPA as a significant predictor. Entry of GPA into the logistic regression model significantly improved model fit (null –2LL = 31124.25, χ^2 = 5766.33, $p < .001$). As displayed in Table 4.7, odds of student success increased with each categorical level of cumulative GPA. Odds of success among students with a 4.0 GPA were 90.68 times that of students with a GPA lower than 1.0 (OR = 90.68, 95% CI = 68.96, 119.25).

Table 4.7 Logistic regression results, predicting likelihood of success based on cumulative GPA.

	B	SE	Wald	df	p	Odds Ratio	95% CI for OR Lower	Upper
CUM GPA			4368.026	4	.000			
CUM GPA 1.00-1.99	.750	.112	44.637	1	.000	2.116	1.698	2.637
CUM GPA 2.00-2.99	2.309	.099	543.496	1	.000	10.060	8.285	12.215
CUM GPA 3.00-3.99	3.809	.100	1445.662	1	.000	45.107	37.066	54.893
CUM GPA 4	4.507	.140	1040.385	1	.000	90.684	68.957	119.256
Constant	-1.844	.097	364.111	1	.000	.158		

The resulting model is:

$$\text{Logit}(\hat{Y}) = -1.844 + 0.750\,X_1 + 2.309\,X_2 + 3.809\,X_3 + 4.507\,X_4 \tag{4.1}$$

where $\hat{Y}$ is SUCCESS,

X_1 is the count of students with cumulative GPA falling into the category of 1.00-1.99

X_2 is the count of students with cumulative GPA falling into the category of 2.00-2.99

X_3 is the count of students with cumulative GPA falling into the category of 3.00-3.99

X_4 is the count of students with cumulative GPA of 4.00

Exploring whether a particular combination of variables could be used to predict success was more challenging. First, entering all Phase One variables into a single logistic regression model proved unsatisfactory, because certain variables were incompatible. For example, students admitted to an associate-level degree program would never be enrolled in graduate level courses. As another example, non-degree students, graduate students, and students located outside Fairbanks could never be categorized as

Student Athletes. Further, the variables of class standing and degree level showed multicollinearity because both included a category for non-degree-seeking students. Therefore, to address the question of whether combinations of variables could effectively predict success in online courses, it was necessary to run logistic regression on subgroups rather than the whole dataset.

Returning to results of the crosstabs, class standing produced the second largest effect size after cumulative GPA. Dividing the dataset into subgroups by class standing produced a rational way to address multicollinearity and incompatibilities among variables, as many of these issues involved class standing. Therefore, logistic regression analyses were conducted for each class-standing group, using the Forward Conditional entry method. This series of analyses confirmed that the variables contributing to student success differed among the various levels of class standing. Table 4.8 displays the summary of predictor variables for each class standing, obtained through logistic regression.

Table 4.8 Predictor variables for each class standing.

	Age	Athlete	Class Size	Degree Level	eLearning Only	Gender	Financial Aid	First eLearning	Full-time Student	Cum GPA	Location	Race
Non-degree					■	■		■		■		■
1st time Freshmen									■	■	■	
Other Freshmen		■	■	■		■				■		■
Sophomores		■	■	■						■		■
Juniors	■	■				■	■			■		■
Seniors	■		■		■	■	■	■	■	■	■	■
Grad Students	■								■		■	

Table 4.9 summarizes logistic regression results for each class-standing model. For non-degree students, a five-factor model explained 12.9% of variance, increasing accurate classification of cases from 65.2% to 78.1%. The five-factor model for non-degree seeking students included cumulative GPA, gender, race, first-time eLearning, and eLearning courses exclusively. For first-time freshmen, a three-factor model including cumulative GPA, student location, and full-time student status explained 17.8% of variance. For other freshmen, a six-factor model explained 13.6% of variance. The six-factor solution for other freshmen included cumulative GPA, gender, race, UA Athlete, class size, and degree level. Improvements in classification fell off more and more for each successive class standing group. For graduate students, the predictive model

explained almost no variance. Full models for each class standing are included in Appendix E.

Table 4.9 Logistic regression results for each class standing model.

	Block 0 Classification	Block 1 Classification	% Variance Explained	Beg. -2LL	Chi-Square	End -2LL	df	Significance Level
Non-degree	65.2	78.1	12.9	3219.533	821.221	2398.312	12	0.000
1st time Freshmen	64.8	82.6	17.8	1388.605	550.962	837.643	9	0.000
Other Freshmen	62.7	76.3	13.6	5429.550	1450.929	3978.621	18	0.000
Sophomores	73.9	78.0	4.1	6082.679	1116.100	4966.579	17	0.000
Juniors	74.3	77.0	2.7	5979.806	985.594	4994.212	18	0.000
Seniors	77.7	79.0	1.3	7949.841	1072.813	6877.028	28	0.000
Grad Students	92.1	92.1	0.0	566.085	44.527	521.558	9	0.000

Phase Two Results

Phase Two continued the investigation of success among online students at UAF by collecting additional data from a subgroup of the Phase One population. Phase One included enrollments over an eight-semester period; the population for Phase Two was narrowed to a single semester. In addition to the narrowed population, the case unit for Phase Two also changed. Whereas Phase One considered each distinct enrollment a case, Phase Two shifted to evaluate each discreet student as an individual case. 2,581 students who had taken one or more UAF eLearning courses during the Spring 2015 semester were invited to complete an online questionnaire. 320 students submitted the questionnaire, producing a response rate of 12.4%. After removing 17 responses due to errors or incongruity, Exploratory Factor Analysis (EFA) was performed to identify related questions and thereby create a factor structure.

Exploratory Factor Analysis (EFA)

Prior to EFA, the data were examined for suitability. The correlation matrix revealed values greater than 0.3 for all 60 coefficients, indicating enough commonality to justify factoring (Beavers et al., 2013). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.918 and Bartlett's test of sphericity was significant at the 0.001 level, lending further evidence that the data were suitable for factor analysis (Tabachnick & Fidell, 2007; Williams et al., 2010). Principal Axis Factoring (PAF) was used for extraction, congruent with the intent of exploring constructs that cannot be measured directly (Beavers et al., 2013; Brown, 2006). Additionally, when evaluated against the results of Principle Component Analysis (PCA) on this dataset, PAF provided a cleaner solution. Initial extraction produced ten factors with eigenvalues above 1.0.

After visual examination of the scree plot, eight factors were retained. Oblimin rotation was performed to aid in interpretation of factor loadings. The eight-factor solution explained 64.4% of variance and revealed a simple structure with more than three moderate-to-strong loadings on each factor and with minimal cross loading (Costello & Osborne, 2005). Further, the structure was consistent with the instruments originally combined to create this assessment. Three subscales from the Multidimensional Scale of Perceived Social Support (MSPSS) were identified as separate factors in this analysis: Perceived Support of a Special Person, Perceived Support of Friends, and Perceived Support of Family.

Cronbach's Alpha

Cronbach's Alpha provided evidence of good internal consistency for each of the extracted factors, with alpha scores ranging from 0.83 to 0.97, as shown in Table 4.10.

Table 4.10 Cronbach's Alpha scores for eight identified factors.

	Alpha Score
Perceived Academic Control	0.827
Mindset	0.943
Self-Efficacy	0.918
Perceived Social Support of a Special Person	0.967
Perceived Social Support of Friends	0.894
Perceived Social Support of Family	0.879
Teaching Presence	0.966
Social Presence	0.911

Preliminary evaluation of Phase Two data revealed a response bias weighted toward *successful* students who earned a final course grade of C- or higher. Only 41 of the 303 Phase Two responses came from those who did not complete their online course successfully. The low response rate among those categorized as unsuccessful made it unlikely that statistically significant conclusions could be drawn about that group. Therefore, Phase Two analyses were conducted exclusively on responses from successful students. With this change, the binary criterion variable of success/non-success used for

Phase One was no longer applicable. Instead, the criterion variable became final course grade evaluated at the ordinal level: C-, C, C+, B-, B, B+, A-, A, or A+. Five participants who had received a "P" grade were therefore removed, leaving 257 respondents who earned final course grades of C- to A+.

Each question in the Phase Two assessment that related to a psychological, psychosocial, or educational construct had been measured at an ordinal level (e.g., Likert score of one-to-five). After eight factors were identified via EFA, a total scale score for each participant on each factor was calculated. Total scale scores for each of the eight factors showed negative skewness. The assumption of normal distribution was violated for all scales, as confirmed by Shapiro-Wilk's test ($p < .01$). As a result, nonparametric tests were used for all subsequent analyses of association. In order to create meaningful groups for associational analysis, each scale score for each participant was categorized with a binary value of high/low. Due to the substantial level of skewness, mean scale scores of 4.0 to 5.0 were categorized as "high" while scores below 4.0 were classified "low."

Somers' delta was chosen as a nonparametric measure to assess strength and direction of the association between final grade and each of the eight constructs measured by the Phase Two questionnaire. Unlike other common tests of association between ordinal variables, Somers' d allows the dependent variable to be distinguished from the independent variable. Three of the eight constructs were found statistically significant: teaching presence, perceived academic control, and perceived social support of a special person. High perceived academic control showed the greatest effect size among the three. With final grade as the dependent variable, 30% of the variation in final grade was explained by the variation in perceived academic control. Other results are presented in Table 4.11.

Table 4.11 Somers' delta results.

	Somers' d	Approx. Sig.
High Perceived Academic Control	.299	.003 *
High Incremental Theory Mindset	-.011	.877
High Self-Efficacy	.122	.096
High Social Support of Special Person	.161	.048 **
High Social Support of Family	.064	.358
High Social Support of Friends	.089	.197
High Teaching Presence	.181	.007 *
High Social Presence	.120	.095

* significant at the $p < .01$ level

** significant at the $p < .05$ level

Scale scores with a statistically significant correlation to final grade were subsequently assessed by means of Mann-Whitney U tests. While Social Support of a Special Person was shown statistically significant in the Somers' d test, it did not reach statistical significance when evaluated with the Mann-Whitney U Test ($p = .052$). Significance was confirmed for the scales of perceived academic control (PAC) and Teaching Presence.

The Mann-Whitney U test was conducted to determine whether there were differences in final grade between students with high PAC (defined by a mean scale score of 4.0 to 5.0) and students with lower PAC. Distributions of the final grades for these two groups were not similar, as assessed by visual inspection of the histograms. Therefore, mean rank is reported rather than the median (Laerd Statistics, 2015). Final grades among students with high PAC (mean rank = 134.38) were statistically significantly higher than among students with lower PAC (mean rank = 95.94), ($U = 2788.000$, $z = -3.013$, $p = .003$).

A second Mann-Whitney U test was conducted to examine differences in final grade between students who reported high teaching presence in the course (defined by a scale score of 4.0 to 5.0) and students who reported lower teaching presence. Again, distributions of the final grades for these two groups did not appear similar when assessed visually. Final grades among students who reported high teaching presence (mean rank = 139.87) were statistically significantly higher than among students who reported lower teaching presence (mean rank = 116.59), ($U = 6730.500$, $z = -2.623$, $p = .009$).

Three additional variables collected during Phase Two were nominal rather than ordinal and, therefore, were assessed via crosstabs rather than Somers' d. The three Phase Two variables examined via crosstabs were Student Employment, Time and Effort Spent Caring for Family Members, and whether a Parent had Graduated College. Initial attempts to assess significance of these variables via chi-square violated the assumption of expected frequency count for each cell. To address this issue, final grades were collapsed into three categories: A, B, and C. None of these variables revealed a statistically significant association with final course grade.

Table 4.12 Chi-square and phi among Phase Two circumstantial variables.

	Pearson Chi-Square	df	Asymp. Sig. (2-sided)	Phi
Work Status	8.851	4	.065	0.186
Caring for Family	1.180	2	.554	0.068
Parent College Graduate	3.775	2	.151	0.121

Combined Quantitative Results

Research Question 1

To what extent do personal variables account for student success in asynchronous online courses at the University of Alaska Fairbanks? Three personal variables were shown to have significant relationship with course success and a practical effect size: cumulative GPA, race, and perceived academic control. Of the three, cumulative GPA revealed the largest effect size. By contrast, race demonstrated the smallest effect size.

Research Question 2

To what extent do circumstantial variables account for student success in asynchronous online courses at the University of Alaska Fairbanks? Statistical analyses revealed a significant and practical relationship between success in online courses and two circumstantial variables: class standing and degree level. For both variables, the effect size was relatively small.

Research Question 3

To what extent do course variables account for student success in asynchronous online courses at the University of Alaska Fairbanks? Two course variables revealed a significant association with success in online courses: course level (e.g., lower division, upper division, or graduate level) and teaching presence.

Research Question 4

To what extent can a combination of personal, circumstantial, and course variables be used to predict success in asynchronous online courses at the University of Alaska Fairbanks? Subgroups were created, organized by class standing, to evaluate predictive capacity of variable combinations. Logistic regression yielded predictive models for each level of undergraduates. The most substantial improvement in accurate classification (prediction) was achieved for freshmen and non-degree-seeking students. Improvements in classification models fell off with each successive year of student experience. At the graduate level, there was almost no predictive value in the logistic regression model.

Phase Three Results

To complete this mixed-methods study, qualitative data were collected via personal interviews with twelve students. Guided questions included in the interview protocol led to discussion of the following questions:

5. How do successful online students perceive the impact of personal, circumstantial, and course variables in their educational experience?
6. How do successful online students define their role versus the instructor's role and how does each role contribute to student success?

7. How have successful online students been able to overcome challenges and persist to completion?

Although results of qualitative research are not generalizable, they provide deeper, context-specific insights that cannot be obtained through quantitative means alone. In the explanatory sequential design employed for this study, qualitative methods were used to explore perspectives of students with a variety of characteristics and circumstances. Interview results provide a sample of student voice, revealing what they considered important to their own success and describing elements of success in their own words.

Interview Participants

This section presents a brief description of each participant with a snapshot of interview highlights. Pseudonyms have been used to protect individual identity. Highlights are followed by a summary of themes that emerged during the interviews.

Adam. Adam was a working adult over the age of 24, classified in the university information system as a non-degree-seeking student. He had previously earned a masters degree in economics. During the timeframe of this study, he was taking a calculus course to improve his math skills and to finish a graduate certificate in statistics. Adam was not entirely satisfied with the online math course. For him, success was synonymous with understanding, and he did not gain the understanding in this course he had hoped for. In his opinion, the course focused too heavily on working large sets of homework problems and did not include enough presentation.

Beth. Beth was also classified as a non-degree-seeking student, but was at the other end of the educational spectrum. In contrast to Adam, who had already earned a graduate degree, Beth was a high school senior trying to get a head start on college by taking general education requirements prior to college admission. During the research period, she took a statistics course for *dual credit*—completing a high school course requirement and earning college credit with the same course. She was 18 years of age at the time. During the interview, Beth particularly emphasized the importance of engaging with the instructor. When discussing the online student's role she said, "online, the student has almost more of an obligation to be proactive in taking more control of their education; that is just one of the responsibilities that comes with the privilege of taking an online class." She went on to describe proactive behavior as making time for studying, troubleshooting technology issues, remembering due dates, and asking direct questions of the instructor. Throughout the interview, she talked about using all resources at her disposal: the textbook, online websites, her parents, and high school teachers. But above all, she stressed the importance of initiating contact with the professor.

Chloe. Chloe expressed pride in being an Alaska Native, originally from the Aleutian Islands. At the time of this study, she was a traditional freshman, under the age of 20 and living on campus. Chloe's major was Alaska Native studies, with a concentration in Alaska Native Law and Politics. Her ultimate goal includes law school. Like Beth, Chloe repeatedly mentioned contact with the instructor. In fact, she recommended contacting the instructor before getting started in a course. During the spring semester of her freshman year, Chloe took a science course online as one of her general education requirements. She commented throughout the interview that the instructor for this course was responsive, available, flexible, and understanding. She mentioned contact with the instructor via phone, email, and individual Blackboard

Collaborate sessions. However, she also asserted that online students teach themselves, saying, “In the online class, you’re both the teacher and the student.” She described an in-person instructor’s role as teaching students and explaining content. By contrast, she portrayed the online instructor as one who provides students “with the tools and resources to teach yourselves.” Chloe noted she was a slow reader and that reading was the most difficult part of the course for her.

Debra. Debra was a non-traditional freshman in her 30s seeking a Certificate, and later an Associate Degree, in Early Childhood Education. She was a stay-at-home mother of two teenage children and additionally provided care for two nephews 12 hours per day. Debra’s focus on degree completion was evident—she returned to that topic several times during the interview. When describing success, she mentioned course grade briefly, but emphasized that each completed course was another milestone toward her goal of graduation.

Ethan. Ethan was a full-time student under the age of 20, living at home and working part time while attending college. In Spring 2015, he was a sophomore at UAF. Throughout the interview, Ethan described himself as independent, self-motivated, and driven. He was attempting to finish a four-year degree in three years and consequently added one or two online courses to his campus-based courses each semester to maximize his schedule. Ethan expressed a preference for taking specific courses online, rather than in the classroom, because he was inherently more interested in the subject and so felt more self-motivated to pursue learning independently. Of those subjects he said, “I’ve always considered myself to be [a] strong self-learner and I like to pick up new things and learn about new things outside of the classroom setting.” And again, “a large part of it is my preference for being able to teach myself in a sense and learn what I feel is important and be able to go over things as many times as I need to." Ethan opined that online courses help students to develop self-regulation skills that are valued in the workplace.

Faye. Like Ethan, Faye was also a sophomore under the age of 20 living at home while attending college. She was working full-time, going to school full-time, and caring for her younger brother and sister in the evenings while her parents worked. Because she previously had trouble with the freshman chemistry class required of science majors, she decided to give herself a refresher by taking an online chemistry course that met the general education requirement for non-majors. She purchased the teacher's edition of the textbook because it provided more information than the student version; she also used other old textbooks as resources. (After taking the online non-major course, she passed the face-to-face, two-course Chemistry sequence required of science majors.) Faye described the stress resulting from family finances and the responsibility she shouldered to help out. She found that e-books were a cheaper alternative to printed textbooks and used them whenever possible because, "less stress for money really meant less stress on passing my class."

Gina. Gina was a student athlete and an Elementary Education major who was attending UAF full-time; she was a junior at the time of this research. Gina mentioned that student athletes often take online courses because these classes work well with team travel schedules. Gina's experience from a young age of balancing sports and extra-curricular activities with school helped her to practice the type of time management that college requires. She advocated using a student planner to record due dates for all courses—both online and classroom. Unlike some of the other interviewees who highly prized independence, Gina appreciated the social interaction and input from classmates in the online discussion forums. She also spoke about the positive influence of being surrounded by people with like values. Her teammates, in particular, had a positive influence because, "we take a lot of pride in having good grades as a team."

Haley. Haley was a working, single mother in her early 20s. She began college shortly after high school and accumulated a number of credit hours, but then took a break from college and got married. When she returned to the university, she was working full time and independently raising two children under the age of five. Upon readmission to the university, she shifted her degree program and her academic goals. So, although she was classified as a junior, she was taking entry-level courses—working toward three occupational endorsements, a certificate program, and then an associate degree. She described the challenges associated with her circumstances, saying

> A lot of my homework time is in the evening, so after I put my kids to bed, that's when I do my homework…it's not always ideal, but… that's why I chose online classes I guess, so that I could spend my late evenings working on it whenever my house is quiet.

She discovered she could handle two courses per semester and maintain good grades.

Ingrid. Ingrid was a geoscience major who took an online political science course as a senior. She chose online because she was working and needed the flexibility; she chose to take the political science course online because it was a general education requirement and not part of her major—she was less interested in the topic. Ingrid talked at some length about the discussion forums. Because the course required original weekly posts as well as responses to other students, she learned to prioritize the discussion assignment and post early; otherwise "your idea was already taken." Speaking about the requirement to engage in discussion she said, "I think that did remind me of the value of listening to other people, listening to your fellow classmates, because… in a lot of lecture-based in-person classes, you don't really get that as much." From the online experience, she learned that "everyone has something to offer you." She subsequently tried to increase her collaboration with other students in classroom courses as well.

Janet. Janet was in her 40s and returning to college after a military career and some time as a stay-at-home mom. Although she had earned a bachelors degree in civil engineering years earlier, she was classified as a senior because she applied for admission to another bachelor degree program at UAF. Her goals shifted and she decided to pursue a Masters in Elementary Education instead. She was taking a graduate-level education course that was only offered online, along with three other courses, during this research period. She recalls that it was a challenging time for her family. She had two elementary-age children. She and her family had just moved back to Fairbanks upon her husband's retirement from the Air Force. He was beginning a new job that required travel, so she felt like a single parent when he was away. Janet described herself as "pretty self-sufficient." She credited her experience as a military officer for preparing her to be organized and responsible. During the interview, she repeatedly referenced the need to map out course requirements and deadlines. She spoke about being partially her "own teacher" by saying, "The instructor kind-of sets a path for you and you have to move yourself along that path," and later, "you really have to drive that train yourself."

Karen. Karen was a graduate student in her mid-30s, completing an online Masters of Justice. She selected UAF's online degree program intentionally because it culminated with a weeklong face-to-face intensive. She expressed some concern about the stigma of fully online degrees, but felt the intensive addressed that issue. Karen was facing medical challenges: she was a recent cancer survivor, still receiving follow-up treatment, who discovered she was pregnant during the semester investigated in this study. Adding to the chaos, as she described it, she was both working full-time and going to school full-time. Additionally, her husband was an active-duty military member. Karen attributed her success to strong organizational skills, determination, and "working really, really hard."

Laura. Laura was a graduate student in her late 20s, finishing up her teaching certification and beginning a Masters of Education program. Among the topics that Laura discussed, she particularly emphasized flexibility. She took the course online because her work schedule did not allow for a rigid commitment to classroom attendance. However, the class was stacked with an in-person course, so she was able to attend in person on several occasions. She mentioned both work and personal circumstances (for example, the birth of her child during one semester) in which the flexible nature of online learning was critical to her success. Laura talked about the egalitarian nature of online discussion forums that seemed to level the playing field for diverse voices. She contrasted that to classroom experiences where some personalities seem to dominate the discussion. However, she acknowledged that strong writing skills were paramount in a medium where most discussion takes place in written form.

Themes

Six strong themes emerged during Phase Three coding and analysis: Time Management, “Teach Yourself,” Student Initiative, Supportive Family, Teaching Presence, and Social Presence. Virtually all students commented on the flexibility of online courses. However, in most cases, flexibility was not an antecedent to their success but rather an explanation for why they chose the online format. In some cases, however, students spoke of an individual professor’s flexibility in accommodating extenuating circumstances.

Time management. Each of the interview participants identified time management as a critical component of success in online courses. Many tied time management to scheduling. As Debra explained, in a face-to-face class the schedule is set for you: “You have to be at class from 9:00 am until noon, and during that three-hour block that’s where you are. You’re in class.” Whereas, online, “you have the entire week to figure out your time allotment of what you’re going to do and how and when…” Several students noted how easily online homework deadlines can slip your mind when you are not physically in a class to be reminded of due dates. Gina addressed the related problem of procrastination:

> I also tried to really budget my time well and not leave my online class assignments until the end because I feel like those are easier to procrastinate because you don't have a professor or people in your class reminding you that things are due.

Chloe, Gina, and Laura all described their use of student planners to manage homework and deadlines. Ingrid and Karen talked about creating master calendars of assignments and due dates. Beth blocked off time each morning and worked on her online course as if she were attending a class in person. Chloe set aside a specific day each week to complete online course assignments. In addition to scheduling and time allocation, participants linked time management with organization and prioritization. Faye described her experience in online courses by saying,

> It has taught me a lot about time management, but it also has taught me better organization skills. I was able to pick and choose which assignments were due sooner, but also which ones required more time. So if something was due soon but it didn't require a lot of time, I would do something else that required more of my time but was due maybe a few days later.

Similarly, Janet said, “It was just a matter of finding a routine and mapping out when course work was due for every class and prioritizing what I needed to do to meet the next deadline.” She described her approach to the process, saying,

> I go through every syllabus and I make a consolidated ‘to do’ list and a spreadsheet, and I sort it by date so that things are listed in chronological order…then I use the ‘to do’ list to literally check off every item as I get it done.

Teach yourself. Four interviewees used some variation of the phrase “teach yourself.” The phrase appeared to hold multiple meanings. Related to time management and scheduling, Faye said,

> …obviously we are the student, but I think when it comes to the online course, we're also the professor because we have to teach ourselves, especially when it comes to a course that was as open-ended learning (*sic*) and self-driven as CHEM 100 was online for me.

She added, “It was very student-paced and I think that kind of put the student in the professor's position. You taught yourself.” Janet’s comment about moving herself along the path set by the instructor was similarly framed in the context of self-pacing and self-direction. Speaking of a face-to-face course she said, “You are getting those academic conversations. You are getting reminders. You might be getting bits of information from other students on things that you missed.” She then contrasted that environment to the online situation, saying, “When it's online and you're not meeting regularly and may never meet any of the other students or the instructor, you really have to drive that train yourself.”

Chloe addressed the same meaning as Faye and Janet with her comment, “in the online class, you are both the teacher and the student. There’s no one there. I mean, you’re kind of your own supervisor and there’s no one to remind you that you have assignments to do.” However, she went on to expand the meaning of teach yourself by saying, “No one’s going to be there to really actually explain. You can’t go to the classroom and expect the lesson to be gone over that day.” When asked later in the conversation whether the role of the instructor was different online than in the classroom, Chloe began by saying, “Well, in class they do better with explaining because you can see what’s going on. There’s a different sort of interaction that happens when two people are physically together.” While she found it difficult to describe the exact difference, she said “in an online class, they provide you with the tools and resources to teach yourselves pretty much.” In those statements, Chloe seemed to juxtapose verbal explanation with written explanation.

Although not using the phrase "teach yourself," other students also addressed differences between spoken and written communication. Beth compared the content delivery of two different online courses she had taken. "In my pre-calculus class," she said, "the instructor always had a screencast that she would upload where she would basically teach the lesson as if she was teaching it on a whiteboard…there was voiceover as well." She then related, "The STAT class didn't have that, which was kind-of disappointing. He would send out lessons that were summaries of the chapter, essentially, which were a little more difficult to follow than the screencast." Likewise, Ingrid talked about lectures that one of her instructors recorded, saying,

> Sometimes you get exhausted from just reading, reading, reading—never hearing someone's voice and never hearing it summed up in a really nice way…so I really liked that, but that wasn't something that was typical in my other online classes.

Debra and Ethan's comments on instructor role were similar to Chloe's. Debra said of online instructors, "They are there to not give you the answers but to give you the tools so you can find the answers yourself." Ethan also thought the role of an online instructor was "more of a guidance and an advising role, not necessarily as much in the delivery role." He later added, "They're not necessarily actively delivering the information on a multi-weekly basis like face-to-face traditional classes would be." Debra and Ethan disagreed on whether the online instructor's role was the same or different than the role of a classroom instructor—Debra contended it was exactly the same as the role of a classroom professor, while Ethan thought it was somewhat different. Nevertheless, both valued independent research and discovery. Debra appreciated the instructor's responsiveness when she asked questions, but she also learned to do some research on her own rather than contacting the instructor immediately when she did not understand something. Ethan found it more interesting to learn certain subjects on his own and felt online courses were geared for students who liked to "self-teach," as well as for non-traditional students and students at a distance. Together with self-paced scheduling and written—as opposed to verbal—explanation, students seemed to embed the idea of independent research into the concept of "teaching yourself."

Student initiative. Student initiative was a common theme in the interviews, although participants used a variety of terms to describe it. Some talked about self-motivation, "being driven," or being a "self-starter," while others called it "being proactive." Ethan reflected that perhaps a higher level of responsibility was required of an online student because of the amount of self-regulation required.

Initiative was exemplified when students proactively reached out to the instructor. As Karen put it,

> I feel like I had a lot more success when I was corresponding with the professor more just to keep a relationship going or touch base a little bit rather than just reading what the assignment was, doing the assignment, and turning it in. I felt like I got a lot more out of the class.

Beth also commented, "I was in constant contact with the professor." According to her description, Beth initiated much of that contact. She summarized her thoughts on this by saying,

> The student has to be a lot more proactive when it's an online class…especially students who wouldn't typically ask questions in class or really engage with the

> professor. [Online] you have to be more engaging because there's no other students that are sitting in the environment around you that you can listen in on.

Likewise, Chloe recommended, "Always contact the professor and make sure the professor knows you. If you have any problems, email them immediately."

Both Ingrid and Gina expressed the opinion that online students choose whether to do the bare minimum or to pursue deeper levels of understanding. Gina characterized this by saying, "for online classes, you get as much out of them as you are willing to put into them." Initiative manifested in the amount of independent work a student was willing to do. Beth said, "I did a lot of extra time studying on my own in the textbook (*sic*) just trying to work out how different formulae and stuff work." Later in the interview, she re-emphasized the time she invested in extra reading and practice, "really, just using all of the resources that I had available to me." Faye secured a teacher's edition of the text as well as other old textbooks to deepen her understanding. Adam commented, "you have to be resourceful at getting material outside of the textbook…being able to look things up is very important."

Supportive family. All twelve students who were interviewed acknowledged the importance of family support. Four of them said their parents occasionally provided homework help. For example, Adam said, "If I had any actual problems that I wasn't able to figure out easily, I would go to my dad for some help. He had his undergrad in mathematics, so he was a good resource." Likewise, Gina said, "My mom is very good at revising papers, so I still enlist her help from time to time for that." But, Gina more strongly emphasized that her parents helped her to value learning. She remarked, "They really kind-of put that passion in me to do well." Other families provided logistical support rather than homework help. As a single mom, Haley commented on the help she received from her parents and sister, saying, “They’ll watch my kids while I go take the proctored exams or even just for me to read homework in silence.” Debra and Janet both mentioned that their husbands had picked up additional household responsibility, such as cooking meals. Debra remarked that her teenage children had been phenomenal in their support. Janet’s children were a bit younger—elementary aged—and yet they also learned to take up additional responsibility like packing their own school lunches. Homework became part of their family culture. As Janet described, “These days, a lot of times, I’m sitting at the kitchen island with them, doing homework right alongside them.” Aspects of practical help notwithstanding, participants mentioned emotional support and encouragement more frequently than any other type of support. “They always believed in me,” Faye said of her parents. Karen described the power of encouragement, saying, “Maybe you have this passing thought in your head that you think it’s not possible, but you have your parents or your family saying, ‘you can do this, you absolutely can’.” Laura described the simple value of companionship while working toward a goal. “My husband is a really good student,” she said.

> He was going through his masters program at the same time, so it was really nice to schedule [time for schoolwork] together so that we could just stay on track with our own program and just have that time set aside. That was personally really helpful for me.

Teaching presence. While some students seemed to appreciate the self-directed, independent environment of online courses, others expressed frustration with the absence of face-to-face instructor contact. Regardless, all felt the role of the instructor was vital to student success. Faye, who was most vocal about the value of self-pacing, explained, "if it weren't for a professor in an online course and if it was just 'go out and learn on your own,' I probably wouldn't have been as successful." She continued by saying, "I do this whole-heartedly and 100% because there's a real person that's grading my assignments that I have to speak to." Likewise, Ethan, who characterized himself as a strong self-learner, acknowledged that he put more effort into online courses when he knew the instructor. "If I had an online course with a professor that I…knew previously," he said, "I would probably put a little bit more effort into it to try to maintain that relationship that we already have. I don't want to look bad. I don't want to disappoint them."

The vast majority of students expressed appreciation for quick instructor response to their emails. Haley contrasted the level of instructor responsiveness in two of her courses. "I have a professor currently who, when I send him an email, he responds within 24 hours," she said. She went on to describe another class where the instructor did not respond to emails at all. Speaking about the second course she said, "I feel like I don't have a teacher. I have a book and things that are on Blackboard." Janet made a similar comparison with regard to instructor feedback. "The biggest differences between [my previous course] and the classes that I'm taking now are the interaction and the feedback from the instructor." Janet went on to say of her current class,

> There's a lot more feedback from the instructor so it feels more personal. I feel like it's a better experience for me. It's more meaningful for me and I actually enjoy it because I feel like the teacher is actually listening to me and reading what I write and reading it thoughtfully.

Ingrid said she sometimes had to remind herself that she had a professor she could reach out to. Especially in online courses with no recorded lectures she said, “It’s just ‘do this stuff for your grade.’ You’re just reading from the textbook or watching other things that aren’t the professor. It’s really hard to remember that there is one.” Still, she felt she had an advantage in that situation. “I’m able to learn by reading, I guess, more so than other people. Some people are more auditory, so I think those people probably struggle a lot with online classes and never hearing a professor’s voice.”

Haley thought the addition of media made an online course feel more personal, especially if it was the instructor’s own voice or if they included an original PowerPoint. “That means a lot to me as a student,” she said. “I feel like that shows a professor really cares that you’re learning what they’re trying to teach you rather than just relying on the book to teach you.” Even if the professor linked to a YouTube video that someone else made, she still felt the addition of extra resources made the course feel more personal. “Having something that applies what you’re reading to life or to an example…that helps me to understand,” she said. “Somebody’s taken the extra step to find something else to reiterate what we’ve already learned from the text. To me, that makes it feel more like an actual class rather than me doing the work by myself.”

Social interaction. Perceptions of interaction varied widely among the participants. Five students (Adam, Beth, Chloe, Ethan, and Haley) indicated they had no interaction with other students in the online class. However, interestingly, some of those same students talked about required participation in the class discussion board. When pressed for more information, it seemed they did not consider activity on the discussion board the same thing as interaction. Haley characterized it as one-way communication, saying, “like someone is speaking, but it’s not a conversation.” Faye noted that discussion boards were a required activity in some classes. “We had to at least participate with other students via discussions,” she explained. “You would comment on their posts and you would have to sort-of volley conversation…to keep the discussions going within the comments section.” Gina claimed the success of discussion board activity hinged on the expectations of the professor. “I have had some professors where you are required to respond but there is no expectation for what your response looks like,” she said. In those cases, she reported, the responses were mostly shallow statements of agreement or disagreement without rationale or feedback.

Upperclassmen and graduate students seemed to find more value in the discussion boards than underclassmen. Laura noted that she had taken both undergrad and graduate courses online. “Online grad courses have been much richer,” she said. With regard to the discussion board in particular, she commented,

> The variety of perspectives was really nice…[Students] are from all over the state and even outside the state, and they’re taking the course for different reasons, so I think that was pretty neat to just hear from other people and see what they’re doing.

Karen stated that she had built good, collegial relationships with classmates in her online courses. However, those connections seemed to have been solidified during the face-to-face intensive that capped her online degree program. “I still actually speak with them, now that I’ve met them through the last week in the in-person courses,” she said. “I actually still keep in touch with them on Facebook and via email. They’re really good as far as professional colleagues. If I have a question about something specific I can contact them."

Janet had previously taken fully asynchronous courses, but was currently taking online courses that offered weekly online meetings. In one of her current classes, the weekly meeting is optional, although she reported that most students participate regularly. In the second class, the online meeting is required. In comparing these courses to the ones she took previously, she said, "I much prefer the classes I'm taking this semester, because I feel like the other students are my peers. We're, for the most part, all teachers." She went on to describe the course environment, saying,

> We're sharing experiences. We're giving advice. I really feel like that's critical to the learning process because we're not just reading the information and writing about it. We're getting other people's perspectives on it, and when you get someone else's perspective it broadens your own understanding.

Comprehensive Results

Elaborative themes emerging from the interviews fell naturally into the framework for Phase One and Phase Two investigation: specifically, personal, circumstantial, and course characteristics. Three of the six emergent themes related to personal characteristics or actions of the student (Time Management, "Teach Yourself," and Student Initiative). The theme of Supportive Family pertained to student circumstances. Two additional themes—Teaching Presence and Social Interaction—related to course characteristics. Furthermore, Phase Three themes directly aligned with results obtained during Phase Two. In Phase Two of the study, students with higher levels of perceived academic control were shown to earn significantly higher course grades.

Expectancy beliefs related to perceived academic control were born out in the interviews as students discussed time management, student initiative, and ways in which they "taught themselves" in an online course. Interview participants also described perceptions of teaching presence, shown significant in Phase Two, as they discussed elements of their own success.

Phase Three analysis indicated that appreciation for online student-to-student interaction grew with academic experience. Graduate students, in particular, benefited from interaction with their peers, while underclassmen found these discussions less meaningful. Although limited in scope, this lends some support to the Phase One finding that different variables are predictive of success among different class standing groups. In the following chapter, conclusions of these results will be discussed, along with implications for practice.

Chapter 5: Summary, Discussion, and Conclusions

Online course enrollment continues to grow as the post-secondary student population shifts to include an increasing percentage of older, non-traditional students with families and careers. A majority of U.S. universities have embraced the online delivery model in response to student demand for flexible options. Online education has been particularly important in the state of Alaska as a means of increasing student access to higher education. Still, online learning is not accepted completely without reservation; an annual survey of chief academic officers at public, private non-profit, and private for-profit post-secondary institutions revealed perennial concerns over retention rates in online courses (Allen & Seaman, 2013).

Theoretical models agree that student success is contextually sensitive and may be influenced by a combination of elements (Bean & Metzner, 1985; Berge & Huang, 2004; Rovai, 2003; Tinto, 1993). Nevertheless, relatively few studies have examined objective course outcomes of online students in a comprehensive manner that includes personal, circumstantial, and course variables. Those that have attempted to do so have yielded mixed results. Therefore, the purpose of this research was to develop a contextually based understanding of factors that influence online student success within the state of Alaska, by evaluating wide-ranging personal, circumstantial, and course variables in combination.

Summary of Results

A strengths-based, mixed-methods study was designed and conducted to answer seven research questions related to student success in online courses at the University of Alaska Fairbanks (UAF). The first three questions explored association between variables. The fourth question sought to ascertain whether success could be predicted by combining variables. The final three questions pursued viewpoints of successful students, capturing their voices to present a strengths-based perspective of success.

Research Questions 1-3

To what extent do personal, circumstantial, and course variables account for student success in asynchronous online courses at the University of Alaska Fairbanks? Results of this study revealed statistically significant relationships between success in online courses and seven individual factors: three personal variables, two circumstantial variables, and two course variables. Cumulative GPA demonstrated the largest effect size among the seven factors. Other variables shown to be statistically and practically significant were class standing, course level, degree level, race, perceived academic control, and teaching presence.

Research Question 4

To what extent can a combination of personal, circumstantial, and course variables be used to predict success in asynchronous online courses at the University of Alaska Fairbanks? Accurate classification of success was substantially improved in some of the predictive models developed during this study—particularly for non-degree seeking students and freshmen. No combination of variables was shown to predict success more accurately than GPA alone when applied to the entire group of students. However, further analysis indicated that the variables predictive of success changed with students' level of academic experience—lending strong support for the premise that student success is context-sensitive and multi-faceted. Cases were therefore grouped according to class standing and predictive models were generated for each group, with a different combination of predictive variables identified for each class standing.

Research Question 5

How do successful online students perceive the impact of personal, circumstantial, and course variables in their educational experience? During individual interviews, twelve successful online students discussed their experiences and their success. Interviewees' comments about personal characteristics and actions coalesced into themes of time management, student initiative, and the ways in which they taught themselves. Meanwhile, participants' descriptions of their online course experience merged into themes of teaching presence and social interaction. Students described teaching presence as substantially more important to their success than social interaction within the course. Finally, interviewees discussed circumstantial elements of their lives primarily as challenges that were overcome by effective strategies and perseverance—an outlook congruent with an internal locus of control perspective. When asked what role social support played in their success, all affirmed the value of a supportive family (including spouses), while a smaller number discussed support from friends.

Research Question 6

How do successful online students define their role versus the instructor's role, and how does each role contribute to student success? Participants discussed the online instructor's role in contrast to the in-person classroom instructor's role. In face-to-face classrooms, they thought the instructor's role was to lecture and explain, while online, the instructor's role was to guide and provide resources. This description of instructor roles did not necessarily reflect student ideals, but was a description of their lived experience. It followed that several participants said the online student role was, in part, to teach oneself. Three elements of "teach yourself" emerged in their descriptions. First, online students are responsible for their own schedules and effort regulation, to a much greater degree than what is expected of students in classroom courses. Second, online course material is often delivered in written form, while in-class lectures are usually delivered verbally. Some students seemed to equate "teaching" with oral presentation. These students implied that written presentation necessitated "self-teaching." Finally, students indicated that online courses required more independent research than in-person courses.

Research Question 7

How have successful online students been able to overcome challenges and persist to completion? Participants spoke of determination, self-motivation, hard work, help-seeking behavior, and supportive family. Several talked about proactively communicating with the instructor. Most reported that instructors had been willing to accommodate their individual needs when informed of extenuating circumstances.

Advantages and Limitations

The population for this study was intentionally restricted to students who took an online course through the eLearning unit at a single research university. Because variables included in the study represented a broad spectrum of personal, circumstantial, and course variables, this restriction offered the advantage of minimizing extraneous variables. An underlying theoretical framework that emphasized local academic culture further supported this decision. Intentionality notwithstanding, the ability to generalize results to other institutions may be limited. Nevertheless, given the large number of cases and the fact that nearly10% of cases were students outside the state of Alaska, results may prove useful to inform research at other institutions.

Another limitation was the lack of variance among Phase Two respondents. First, successful students responded in disproportionate numbers; the study would have benefited from additional data on non-successful students. Second, the responses of successful students were non-parametric. It is unclear whether all successful online students have an equally high level of perceived academic control, or whether internal locus of control prompted this particular set of students to respond to the questionnaire.

Cumulative GPA for this study was collected at the same time as final course grade, rather than being measured prior to student enrollment. This had implications particularly for predictive models of success among freshmen, as discussed later in this chapter.

As a final limitation, the definition of student success in this study was restricted to final course grades. Once again, this was a deliberate choice in the research design, with the assumption that final grades represent measurable, objective outcomes. However, course grades are not the only valid measure of student success. Additional facets of success, such as student satisfaction or student perception of learning, were not addressed by this research. It is conceivable that using a different definition of success could yield different results.

Connection with Prior Research

This study contributes to existing knowledge regarding student success in online courses. Empirical studies of student success in the online environment have not yet formed a consistent body of evidence. Many variables investigated in prior research were only examined in a single study. When variables were explored in multiple studies, the research often produced conflicting results. The current study indicates that factors related to success may change with a student's level of academic experience. This appears to be a unique and significant contribution that may help to explain some of the contradictions in previous research.

Evidence that different combinations of variables are predictive of success at different academic class levels suggests that student variables are best examined contextually and holistically rather than in isolation. Nonetheless, the current study discovered seven individual factors with statistical and practical significance related to student success in online courses across the full dataset of all class standings. These seven variables are reported below in order of effect size, from largest effect to smallest, with explanation of whether current results support, or differ from, previous findings in the literature.

Cumulative GPA

Results of this study indicate a strong positive relationship between cumulative GPA and online course success, aligning with earlier findings from Aragon and Johnson (2008), Cochran et al. (2014), Hachey et al. (2014), Jost et al. (2012), Harrell and Bower (2011), and Suphi and Yaratan (2012). Among prior studies of online success, GPA produced more corroborating evidence than any other variable. The current study lends additional support: logistic regression analysis revealed cumulative GPA to be a stronger predictor of student success than any other variable examined in this study.

Perceived Academic Control

As described by Bandura (1991), *locus of control* is concerned with whether an individual believes outcomes are determined by their own actions (internal locus of control) or by forces outside their control (external locus of control). Locus of control has been demonstrated as a predictor of academic success in numerous studies related to traditional classrooms (Perry et al., 2001; Stupnisky, Perry, Hall, & Guay, 2012). However, as reviewed in Chapter 2, locus of control has shown mixed results among studies of online students. The PAC scale used in this study is domain specific, developed to assess college students' beliefs about academic success (Perry et al., 2001). Results of this study indicates students with high PAC scale scores earn higher course grades than students with lower PAC scores. This finding adds to the evidence that internal locus of control is associated with success in online courses (Lee et al., 2013; Rogers, 2015).

Teaching Presence

The current study examined two elements from the Community of Inquiry (CoI) process model developed by Garrison and colleagues (2000). CoI comprises three dimensions: social presence, teaching presence, and cognitive presence. This study measured students' perception of social presence and teaching presence, but did not include cognitive presence. Results revealed final grades to be higher among students who reported high teaching presence than among students who reported lower teaching presence, in agreement with findings by Rockinson-Szapkiw et al. (2016). This finding suggests that success rates in online courses might be improved by increasing practices related to teaching presence.

Class Standing

Findings in the current study indicate that class standing has a statistically significant relationship with success in online courses. Graduate students were shown to have the highest course success rates. Seniors had the second-highest success rates, followed (in descending order) by juniors, sophomores, non-degree-seeking students, first-time freshmen, and continuing freshmen. These results add to evidence for an association between class standing and success, as reported by Cochran et al. (2014) and Levy (2007). The discovery that variables contributing to success differed between various class-standing groups was perhaps more noteworthy than the relationship between class standing and success. For example, the combination of variables that predicted success among first-time freshmen differed from variables contributing to success among continuing freshmen. Again, this appears to be a unique contribution to existing research. This finding could have implications for comprehensive student advising and online student support. Awareness of the factors associated with success at each level of academic experience may empower academic personnel to provide more targeted and effective support.

Course Level

Although course level is often associated with class standing, the two are not exclusively linked. Underclassmen occasionally enroll in upper division courses. More frequently, seniors complete a few remaining general education requirements just prior to graduation. Based on the findings related to class standing, it is not surprising that course level was also shown to have a significant, positive relationship with student success in the current study. This appears to be another unique contribution to the body of knowledge; course level was not examined as a variable in any of the literature reviewed.

Degree Level

Contrary to findings reported by Park and Choi (2009), Wang et al. (2013), and Yukselturk and Bulut (2007), results of the current study indicate a significant relationship between degree level and online course success, although the effect size was small (phi = 0.113). Because this association has not been found in prior research and, in fact, contradicts results of previous research, it may be an anomaly of the population studied here.

Race

This research revealed a statistically significant association between race and success in online courses, again with a small effect size (phi = 0.109). Previous studies produced mixed results with regard to race or ethnicity. Several found no relationship with student success (Aragon & Johnson, 2008; Gibson et al., 2010; Harrell & Bower, 2011; Jost et al., 2012). Some, however, found race combined with other factors yielded a significant association with success (Cochran et al., 2014; Rockinson-Szapkiw et al., 2016; Suphi & Yaratan, 2012). Race was included in all but two of the predictive models developed in this research. Among first-time freshmen and graduate students only, race did not improve prediction of success.

Discussion

Cumulative GPA was by far the strongest predictor of final grade success in online courses, lending support for the conclusion that students who have previously done well academically are more likely to do well in online courses too. Nevertheless, online course completion rates are consistently reported to be lower than face-to-face completion rates, begging the question of whether online students are a different population (with different personal characteristics and circumstances) or whether the courses themselves account for the difference in success rates.

The theory underpinning this research suggested that evaluating personal, circumstantial, and course variables in combination would prove more contextually relevant and useful than evaluating single variables in isolation. Results support that premise. A key finding of this study indicates that factors contributing to student success vary with levels of educational experience. For example, student location and full-time student status contributed to accurate classification of success among first-time freshmen, seniors, and graduate students, while those factors were not relevant in success classification for other class-standing groups. In light of results regarding variable combinations and context, the connections between certain variables in this study merit additional discussion.

Connections Between Academic Variables

Degree level, class standing, and course level are logically connected to one another. Degree level establishes parameters for the logical categories of class standing. Although there are exceptions, a student admitted to an associate-level degree program is not commonly classified with senior-level class standing. Similarly, the connection between course level and class standing was discussed earlier, noting that exceptions to the norm can and do exist. These data points are connected, yet each contributes useful information to the comprehensive picture of student success.

GPA and class standing also bear some relationship, based on the fact that freshmen have fewer completed credit hours with which to calculate cumulative GPA. As reported in the results, logistic regression generated a different predictive model for each level of class standing in this population. GPA was prominent in the models for all class-standing groups except graduate students. Among the generated models, those created for freshmen and non-degree-seeking students explained more variance than models produced for other class standings. Further discussion of cumulative GPA is warranted, because it may have impacted the variance explained among different class-standing groups. In this dataset, cumulative GPA was captured at the same time as final course grade—it was not measured prior to student enrollment. Because freshmen had fewer completed credit hours, the grade on the current course represented a larger percentage of GPA. Impact of GPA on model variance aside, the fact that variables included in the predictive models varied between class-standing groups stands out as a key result of this research.

Connections Between Quantitative and Qualitative Results

Connections between quantitative and qualitative results also deserve further attention. The sequential explanatory design employed in this research, in which qualitative interviews followed quantitative analysis, led to richer understanding of student success. It is pertinent, therefore, to draw clear connections between the most salient elements.

Perceived academic control. The PAC questionnaire, distributed in the second phase of research, assessed students' expectancy beliefs through quantitative analysis of scale scores. PAC asked students to rate their agreement with statements like, "The more effort I put into my courses, the better I do in them." Individual interviews subsequently asked students to reflect on their behavior. For example, interview participants were asked, "How did you achieve success in this course?" and "What is the role of the student in an online course?"

Quantitative results of this study suggest that students who believe they have a high level of control over academic outcomes may earn higher course grades. In the third phase of research, qualitative interviews with successful students reflected the expectancy beliefs of perceived academic control as students talked about time management, student initiative, and the need to teach themselves.

Student statements related to teaching themselves seemed puzzling at first, given that the same students reported online instructors to be instrumental to their learning. When pressed for more information, interviewees revealed three components of teaching oneself in an online class: self-paced effort regulation, independent research, and reading (rather than listening) to acquire information. Effort regulation and independent research are closely related to other themes that emerged from the interviews: specifically, time management and student initiative. The third aspect that students connected with teaching themselves—that of reading rather than listening—aligned with the theme of teaching presence as well.

Interview discussions of reading versus listening revealed interesting distinctions in student perception. Some students implied that "teaching" and "explaining" were inherently verbal activities. When an instructor delivered lecture material in written form, or explained something using text rather than speech, students tended to call the activity "guidance" rather than "teaching." This dichotomy raises interesting questions. It might be construed that reading, by its very nature, is a more active endeavor than listening. However, it is also plausible that students have been conditioned to equate teaching with verbal presentation through past educational experience. Rogers (2015) argued that students have come to expect a lecture format because that is what they have traditionally experienced. As students move from high school to college, they are expected to become more responsible and self-directed (Wadsworth et al., 2007). Nevertheless, unanswered questions about student perceptions of reading versus listening provide an opportunity for further research.

Teaching presence and social presence. Like perceived academic control, student perceptions of teaching presence and social presence were evaluated in the second phase of research through a self-report questionnaire and quantitative analysis of scale scores. Teaching presence was shown to have a statistically significant relationship to final course grade; social presence was not shown significant. During interviews that followed, students were asked, “What role did the instructor play in helping you succeed in this course?” and “How did other students in your online course affect your experience?”

Quantitative results suggest that students who experience a high level of teaching presence in their online course may earn higher course grades. During interviews, students described several elements of teaching presence, such as responding promptly to emails, providing personal feedback on assignments, providing reminders, and recording lectures as audio or screencasts.

Social interaction. When asked, “How did other students in your online course affect your experience?” nearly half the participants responded that they really did not interact with other students at all. Some explained that they did not consider discussion board posts to be interaction. During elaborative coding of interviews, the theme was termed “social interaction” rather than “social presence” because the word interaction was frequently used in student responses. Several students also talked about required group projects; most reported dissatisfaction with group work in the online environment.

Researchers who developed the CoI model, which encompasses teaching presence and social presence, called text-based communication a "lean medium," acknowledging that it lacked the richness of verbal communication. On the other hand, they believed it might be advantageous for rigorous cognitive learning because it slows interaction time and allows opportunity for reflection (Garrison et al., 2000). Graduate students in the current study seemed to support that notion, expressing appreciation for the egalitarian nature of online discussions with peers. By contrast, the underclassmen who were interviewed found discussion board participation less meaningful. Post-hoc evaluation of social presence scale scores among the twelve interviewees confirmed that graduate students rated social presence higher than undergraduates, although the sample size is certainly too small to draw conclusions. Interestingly, the CoI model was originally developed through research on graduate-level courses.

Future Directions

This research study was initiated in response to evidence that chief academic officers at post-secondary institutions express concern over retention rates in online courses, even while a growing number of institutions embrace online learning as a strategy for enrollment growth (Allen & Seaman, 2013). In light of this dissonance, it behooves higher education to actively address issues associated with online student success. Three areas are identified below in which the current research bears practical relevance for post-secondary institutions. In the paragraphs that follow, implications for practice are discussed, beginning with recommendations for higher education administration. This section on future directions concludes with suggestions for further research.

Practical Relevance

The current study provides evidence that factors associated with success change as students gain more academic experience. Specifically, logistic regression revealed that different combinations of variables predict success among each class-standing group. This finding suggests that the needs of freshmen may be different than the needs of graduate students, which may further differ from the needs of non-degree-seeking students. A uniform approach may not be the best way to recruit, advise, support, or teach the broad range of students who pursue online education. As universities seek to operationalize efficiencies in online learning, diversity of student needs might easily be overlooked. Contrary to the one-size-fits-all approach, predictive models generated by this research suggest that student success might be better addressed by considering the unique characteristics and circumstances of students at each level of academic experience.

The current research also provides actionable insight about characteristics of teaching presence, informed by successful students' experience. Students in this study who reported high teaching presence in their online courses earned statistically significantly higher grades than students who reported lower levels of teaching presence. Interviews revealed that students perceive teaching in the online environment to be a different type of interaction than the teacher-student interaction typified in face-to-face classes. Packaged online content, delivered without substantive interaction, does not meet the IPEDS criteria for distance courses (National Center for Education Statistics, 2016), nor does it meet students' needs as described by interview participants. As an example, students indicated that written lecture notes are more akin to textbook readings than to classroom lectures, reinforcing their belief that online students teach themselves through reading. Students emphasized personal communication from the instructor, feedback on assignments, and instructor responsiveness as essential elements of online teaching, equally important to presentation of the content. Because the advantages of enhanced teaching presence may not be readily apparent, the distinction between providing content and establishing effective teaching presence should be explicitly communicated as an element of faculty development.

Finally, this study found that students with high scores on the perceived academic control scale earned statistically significantly higher grades than students with lower PAC scale scores. More importantly, interviews revealed ways in which students with high PAC scores managed their learning experiences in order to achieve success. The opportunity to learn from those who have been successful lies at the core of strengths-based research. Students spoke at length about time management techniques, such as setting aside specific blocks of time for their online course and creating a calendar of assignments. They also talked about taking initiative, proactively contacting the instructor, and using all available resources. Leveraging the information gleaned from these interviews can serve as a springboard to provide students with practical tools. Moreover, student orientations and targeted interventions may help students to recalibrate their perception of academic control and take charge of their learning in a manner that engenders success.

Implications for Administrators

Institutions that wish to grow a strong online program would be wise to invest in student advising and student support services tailored to the needs of online students, recognizing that one size does not fit all. Understanding the combinations of variables associated with success at different educational levels—a key finding of this research—provides an opportunity to enhance student support by addressing success factors specific to each class-standing level. Many of the variables shown significant in this research are academic factors routinely recorded and maintained in university records (e.g., degree level, course level, and cumulative GPA). Other variables, such as race, are commonly collected at the point of admission. Because these factors do not require additional data collection, they provide immediate potential to improve student advising and support services for online students.

The current study found a significant association between teaching presence and online student success, suggesting that effective implementation of online learning should include adequate attention to teaching methods. Institutions that include online learning as a growth strategy would do well to invest concurrently in faculty development and faculty support. Further, faculty workloads should afford the time necessary to maintain teaching presence, thereby encouraging responsive interaction and personalized feedback to students. In the quest for cost-savings, administrators may be tempted to create larger course sections, increasing the student-to-faculty ratio in online courses. Caution is advised, as large-enrollment courses may decrease faculty ability to provide optimal levels of attentiveness to students.

The current study also revealed perceived academic control (PAC) to have a significant positive association with student success. PAC is a latent construct—more complex and less amenable to routine collection than academic factors or personal variables like gender and race. More importantly, however, PAC is distinguished from other personal variables shown significant in this study because it is malleable. While the effort to collect data on PAC may be more challenging, the potential to impact student achievement through data-informed action may also be greater. Students new to online learning might benefit from an orientation or first-year experience that discusses and diagnoses PAC. Because PAC is amenable to change, students with low PAC could be coached to reframe their expectancy beliefs and assume more personal control of their learning environment.

Implications for Faculty

As discussed above, teaching presence was revealed to have a significant association with success. Moreover, successful students underscored the influence of teaching presence during individual interviews. Key elements of teaching presence described by students in this study include instructor responsiveness, personal feedback on assignments, and announcements or reminders. Students revealed that lack of interaction with online faculty sometimes led them to feel they did not have an instructor. Students' descriptions of online course experiences suggest that faculty should be particularly attentive to student communication in the online environment in order promote student success and to rectify the lack of in-person contact.

Students in online courses benefit from knowing that an instructor is personally invested in their success. One student described her appreciation for instructors who make an "extra effort" to include additional resources. The fact that a faculty member has curated appropriate content for inclusion may not be apparent to students. Nuanced changes, such as writing, "I have selected some resources to help you" or "these are some of my favorite resources" may help students to recognize instructor engagement.

Implications for Course Designers

The finding that students tend to perceive written material as impersonal has implications for course design and content delivery. Brief lectures recorded in the instructor's own voice may increase students' perceptions of "being taught" rather than "teaching themselves." Even so, it is clear from this study that student initiative, along with behaviors that students described as "teaching themselves," provide an advantage for online students. Course designers may wish to consider an initial learning module that clarifies expectations for student and instructor roles in the course. Explicit understanding of typical online interactions may assist students who have previously exhibited a more passive approach to learning.

Recommendations for Further Research

The current study generated initial predictive models for student success at each level of class standing. These models of success should be tested on future student cohorts to determine whether the predictive models hold true for future groups. Likewise, it would be useful to examine details of the class standing models more closely. For example, it was interesting that class size improved accurate classification of success in the models for continuing freshmen, sophomores, and seniors, but not for other class standing groups. Because class size constrains the type of student-to-student and student-to-instructor interactions that are feasible in a given course, it would seem applicable at all levels. Additional exploration is warranted.

Results of this study revealed several other areas that might prove fruitful for additional examination as well. First, while quantitative analysis in the current study identified a small effect for race, subsequent interviews did not elucidate that finding.

The process for selecting interview participants in the current study focused specifically on class standing; it did not generate a racially diverse sample. It may be advantageous to explore the association between race and success more fully through additional strengths-based interviews with students representing various races.

Second, as noted in the section on limitations, student response to the online questionnaire was heavily skewed toward successful students. It would be valuable to extend the study to non-successful students, in order to determine whether the variables of perceived academic control and perception of teaching presence differ between successful and non-successful students.

Third, students interviewed for this study drew connections between teaching and oral presentation, classifying verbal explanation as teaching while describing written explanation as guidance. The origin of these perceptions is unclear and ripe for further investigation. Have students simply been conditioned to equate teaching with verbal presentation through past educational experience? This question might be explored by comparing groups of students with various educational backgrounds. For example, perceptions of students who completed high school via home schooling might be compared to perceptions of students who graduated from public or private high schools.

Finally, this study specifically targeted students within the state of Alaska to develop a contextually relevant understanding of success as measured by final course grade. To determine whether results are generalizable to other locations and populations, the study should be replicated in other contexts. Further, other definitions of success—such as student satisfaction, student perception of learning, success in subsequent courses, or success in the workplace after graduation—should be explored to determine whether results differ for these other valid measures of student success.

Conclusion

The purpose of this research was to develop a multi-faceted understanding of post-secondary student success in online courses, within the context of Alaska, by evaluating personal, circumstantial, and course variables simultaneously. The research design employed sequential mixed-method data collection and analysis with a strengths-based perspective. Quantitative results informed selection of a stratified random sample of successful students, resulting in two student interviews from each level of class standing. Twelve individual student interviews reinforced and complemented quantitative findings. Analysis of quantitative and qualitative results together yielded a deeper understanding of issues that would have been difficult, at best, to tease out from either research method alone.

This research added to the current understanding of online student success in three important ways. First, prior research yielded mixed results regarding variables that impact student success in online courses. Although this study identified seven individual variables with statistical and practical significance for online student success, a more significant finding was evidence that success factors appear to change with a student's level of academic experience. This unique contribution to existing knowledge may explain some of the conflicting evidence in previous studies.

Prior research revealed mixed results for an association between perceived academic control and online student success. Prior empirical evidence for association between teaching presence and online student success was scarce. The current study added support for both of those factors. More importantly, however, the mixed-methods nature of this study added depth to the findings. While quantitative analysis produced significant evidence for a positive relationship between perceived academic control and student success, personal student interviews revealed behaviors that students with high PAC exhibit to affect their success. Similarly, quantitative results revealed a significant association between student success and student perceptions of teaching presence, while interviewees' rich descriptions fleshed out practical illustrations of teaching presence in action.

Finally, this research confirmed that personal, circumstantial, and course variables all contribute to student success in online courses. None of these elements should be neglected as higher education tackles the challenge of increasing online student success. Notably, among the different models generated in this study, final grade success was more accurately predicted by a combination of variables than by single variables, further reinforcing the theory that success is indeed multi-faceted. Returning to the original impetus for this study—concern over lower retention rates in online courses—it is important that post-secondary institutions approach online education in a holistic manner, addressing students' personal characteristics and circumstantial barriers while attending to effective teaching practices.

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Appendix A

IRB Approval Letter

UNIVERSITY OF ALASKA FAIRBANKS

(907) 474-7800
(907) 474-5444 fax
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Institutional Review Board

909 N Koyukuk Dr. Suite 212, P.O. Box 757270, Fairbanks, Alaska 99775-7270

January 10, 2017

To:	Barbara Adams Principal Investigator
From:	University of Alaska Fairbanks IRB
Re:	[843443-5] Strengths-based analysis of student success

Thank you for submitting the Continuing Review/Progress Report referenced below. The submission was handled by Expedited Review under the requirements of 45 CFR 46.110, which identifies the categories of research eligible for expedited review.

Title:	Strengths-based analysis of student success
Received:	December 19, 2016
Expedited Category:	7
Action:	APPROVED
Effective Date:	January 10, 2017
Expiration Date:	December 23, 2017

This action is included on the January 25, 2017 IRB Agenda.

No changes may be made to this project without the prior review and approval of the IRB. This includes, but is not limited to, changes in research scope, research tools, consent documents, personnel, or record storage location.

Appendix B

Permissions to Use Assessment Tools

UNIVERSITY of ALASKA

Carol Gering <csgering@alaska.edu>

Request to use Perceived Academic Control Scale

2 messages

Carol Gering <csgering@alaska.edu> Tue, Dec 23, 2014 at 1:31 PM
To: ray.perry@umanitoba.ca

Dear Dr. Perry,

I am writing to request permission to use the eight-item Academic Control Scale from your 2001 paper, Academic Control and Action Control in the Achievement of College Students: A Longitudinal Field Study, as part of my dissertation research. I am studying factors that contribute to success in online courses among postsecondary students in Alaska.

Thank you for your consideration!

Best Regards,
Carol

--
Carol Gering
Executive Director
UAF eLearning & Distance Education
University of Alaska Fairbanks
907-479-4757

Ray Perry <Ray.Perry@umanitoba.ca> Sat, Jan 3, 2015 at 8:54 AM
To: Carol Gering <csgering@alaska.edu>

Dear Ms. Gering: this is to confirm that you have my permission to use my eight item Perceived Academic Control scale for your dissertation. You may also be interested in the attached, recently published article regarding a perceived control enhancing treatment intervention that can be used in online courses to benefit motivationally at risk students.

Cordially,

Raymond P. Perry, PhD

Distinguished Professor of Psychology

Adenauer Fellow, Royal Society of Canada

Co-Director of Emotion, Motivation, and

Control Research (EMCOR) Laboratory

Department of Psychology

UNIVERSITY of ALASKA

Carol Gering <csgering@alaska.edu>

Request to use Theories of Intelligence Scale

2 messages

Carol Gering <csgering@alaska.edu> Fri, Mar 20, 2015 at 10:30 AM
To: dweck@stanford.edu

Dear Dr. Dweck,

I sent an email a couple of months back. I'm trying once more to reach you and hoping I have the right address!

I am writing to request permission to use the Theories of Intelligence Scale—Self Form for Adults in my dissertation research. I am studying factors that contribute to success in online courses among postsecondary students in Alaska.

Thank you for your consideration!

Best Regards,
Carol

--
Carol Gering
Executive Director
UAF eLearning & Distance Education
University of Alaska Fairbanks
907-479-4757

Carol S Dweck <dweck@stanford.edu> Fri, Mar 20, 2015 at 12:47 PM
To: Carol Gering <csgering@alaska.edu>

Sure!

Lewis & Virginia Eaton Professor
of Psychology
Department of Psychology
Stanford University
Jordan Hall, Bldg. 420
Stanford, CA 94305
[Quoted text hidden]

UNIVERSITY of ALASKA

Carol Gering <csgering@alaska.edu>

Request to use Multidimensional Scale of Perceived Social Support

3 messages

Carol Gering <csgering@alaska.edu> Tue, Dec 23, 2014 at 1:41 PM
To: gzimet@iu.edu

Dear Dr. Zimet,

I am writing to request permission to use the Multidimensional Scale of Perceived Social Support in my dissertation research. I am studying factors that contribute to success in online courses among postsecondary students in Alaska.

Thank you for your consideration!

Best Regards,
Carol

--
Carol Gering
Executive Director
UAF eLearning & Distance Education
University of Alaska Fairbanks
907-479-4757

Zimet, Gregory D <gzimet@iu.edu> Wed, Dec 24, 2014 at 4:37 AM
To: Carol Gering <csgering@alaska.edu>

Dear Carol,

You have my permission to use the MSPSS in your dissertation research. I have attached a copy of the scale (with scoring information on the 2nd page) and a document listing a number of articles that have reported on the psychometric properties of the MSPSS.

I hope your research goes well.

Best regards,
Greg Zimet

==

Gregory D. Zimet, PhD

Professor of Pediatrics & Clinical Psychology

Section of Adolescent Medicine

Indiana University School of Medicine

410 W. 10th Street, HS 1001

Indianapolis, IN 46202 USA

Phone: +1-317-274-8812

Fax: +1-317-274-0133

UNIVERSITY of ALASKA

Carol Gering <csgering@alaska.edu>

Request to use Community of Inquiry instrument

4 messages

Carol Gering <csgering@alaska.edu> Tue, Dec 23, 2014 at 2:54 PM
To: arbaugh@uwosh.edu

Dear Dr. Arbaugh,

I am writing to request permission to use the first thirteen questions (related to teaching presence) from the Community of Inquiry survey instrument, as described in your 2008 paper "Developing a community of inquiry instrument: Testing a measure of the Community of Inquiry framework using a multi-institutional sample" in my dissertation research. I am studying factors that contribute to success in online courses among postsecondary students in Alaska.

Thank you for your consideration!

Best Regards,
Carol

--
Carol Gering
Executive Director
UAF eLearning & Distance Education
University of Alaska Fairbanks
907-479-4757

Ben Arbaugh <arbaugh@uwosh.edu> Thu, Jan 8, 2015 at 10:53 AM
To: Carol Gering <csgering@alaska.edu>

Hello Carol, sorry for the delayed reply,

Please feel free to use our COI instrument. Best of luck on your study, Ben
[Quoted text hidden]
--
J. B. (Ben) Arbaugh, Ph.D.
Associate Editor, *Decision Sciences Journal of Innovative Education*
Special Assistant to the Editor, *Online Learning* (formerly *Journal of Asynchronous Learning Networks)*
John McNaughton Rosebush Professor
College of Business
University of Wisconsin Oshkosh
800 Algoma Blvd.
Oshkosh, WI 54901
(920) 203-2647
email: arbaugh@uwosh.edu

Carol Gering <csgering@alaska.edu> Tue, Nov 24, 2015 at 12:31 PM
To: Ben Arbaugh <arbaugh@uwosh.edu>

Dr. Arbaugh,

Thank you for granting permission to use your COI instrument.

I believe you granted permission for the entire COI instrument in your response below; I'm writing to confirm. I originally asked permission to use the first thirteen questions (related to teaching presence) but have since expanded

Appendix C

Phase Two Assessment

Online Student Success

UAF eLearning & Distance Education is interested in learning more about the characteristics of online students. The goal of this study is to learn more about the things that help online students to succeed.

1. **Your decision to take part in this study is voluntary. Whether or not you choose to participate will not affect your grades or any services you receive from UAF. Do you consent to participate?** *
   Mark only one oval.
   - yes
   - no

Page Two

2. **Please enter your UA ID number.** *
   Your name or identity will not be used in any reports.

   ____

3. **Enter the access code from the email you received.** *
   This code will be used to connect your answers below with the course you took and the final grade you received. Your name and identity will be removed before data are reported.

   ____

4. **During Spring 2015 semester, what was your work situation?** *
   Mark only one oval.
   - I was working full time
   - I was working part time
   - I did not have a job

5. **Did either of your parents graduate from college?** *
   Mark only one oval.
   - yes
   - no

6. **During Spring 2015 semester, did you spend significant time and effort caring for others in your family, such as children, siblings, or elders?** *
Mark only one oval.

- yes
- no

Page Three

Please mark the level to which you agree or disagree with each of the following statements.

7. **My grades are basically determined by things beyond my control and there is little I can do to change that.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

8. **My family is willing to help me make decisions.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

9. **Your intelligence is something about you that you can't change very much.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

10. **I have a great deal of control over my academic performance in my online courses.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

11. **No matter what academic challenge comes my way, I'm usually able to handle it.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

12. **If I am in a bind in my courses, I can usually think of something to do.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

13. **I can count on my friends when things go wrong.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

14. **My friends really try to help me.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

15. **I can solve most academic problems if I invest the necessary effort.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

16. **I see myself as largely responsible for my performance throughout my college career.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

17. **When I encounter an academic obstacle, I can find a way to overcome it.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

18. **Thanks to my resourcefulness, I know how to handle unforeseen situations in my academic career.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

19. **I can talk about my problems with my friends.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

Page Four

Please mark the level to which you agree or disagree with each of the following statements.

20. **You can always substantially change how intelligent you are.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

21. **My family really tries to help me.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

22. **There is little I can do about my college performance.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

23. **There is a special person with whom I can share my joys and sorrows.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

24. **I can always manage to solve difficult academic problems if I try hard enough.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

25. **The more effort I put into my courses, the better I do in them.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

26. **I can talk about my problems with my family.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

27. **It is easy for me to stick to my aims and accomplish my academic goals.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

28. **No matter who you are, you can significantly change your intelligence level.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

29. **You can learn new things, but you can't really change your basic intelligence.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

30. **How well I do in my courses is often the "luck of the draw."** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

31. **No matter what I do, I can't seem to do well in my courses.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

32. **No matter how much intelligence you have, you can always change it quite a bit.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

Page Five

Please mark the level to which you agree or disagree with each of the following statements.

33. **When I do poorly in a course, it's usually because I haven't given it my best effort.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

34. **I have friends with whom I can share my joys and sorrows.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

35. **I have a special person who is a real source of comfort to me.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	◯	◯	◯	◯	◯	strongly agree

36. **To be honest, you can't really change how intelligent you are.** *

Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

37. **You have a certain amount of intelligence, and you can't really do much to change it.** *

Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

38. **I can remain calm when facing academic difficulties because I can rely on my coping abilities.** *

Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

39. **I get the emotional help and support I need from my family.** *

Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

40. **There is a special person in my life who cares about my feelings.** *

Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

41. **You can change even your basic intelligence level considerably.** *

Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

42. **There is a special person who is around when I am in need.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

43. **When I am confronted with an academic problem, I can usually find several solutions.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

44. **I am confident that I can deal efficiently with unexpected academic challenges.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

Page Six

The email inviting you to participate in this research study referred to a specific online course. Please mark the level to which you agree with each of the following statements related to that specific course.

45. **What is the name of the course, or the course number, to which your answers relate?** *

____

46. **Instructor actions reinforced the development of a sense of community among course participants.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

47. **I felt that my point of view was acknowledged by other course participants.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

48. **I felt comfortable disagreeing with other course participants while still maintaining a sense of trust.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

49. **The instructor provided clear instructions on how to participate in course learning activities.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

50. **The instructor helped to focus discussion on relevant issues in a way that helped me to learn.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

51. **Online or web-based communication is an excellent medium for social interaction.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

52. **The instructor clearly communicated important course topics.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

53. **Online discussions help me to develop a sense of collaboration.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	⬭	⬭	⬭	⬭	⬭	strongly agree

54. **The instructor was helpful in guiding the class towards understanding course topics in a way that helped me clarify my thinking.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

55. **I felt comfortable participating in the course discussions.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

56. **I felt comfortable interacting with other course participants.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

Page Seven

Still thinking about the same online course, please mark the level to which you agree with each of the following statements related to that specific course.

57. **The instructor helped to keep the course participants on task in a way that helped me to learn.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

58. **The instructor helped to keep course participants engaged and participating in productive dialog.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

59. **The instructor provided feedback in a timely fashion.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree						strongly agree

60. **The instructor provided feedback that helped me understand my strengths and weaknesses relative to the course's goals and objectives.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	( )	( )	( )	( )	( )	strongly agree

61. **I was able to form distinct impressions of some course participants.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	( )	( )	( )	( )	( )	strongly agree

62. **Getting to know other course participants gave me a sense of belonging in the course.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	( )	( )	( )	( )	( )	strongly agree

63. **The instructor clearly communicated important course goals.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	( )	( )	( )	( )	( )	strongly agree

64. **The instructor encouraged course participants to explore new concepts in this course.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	( )	( )	( )	( )	( )	strongly agree

65. **The instructor clearly communicated important due dates/time frames for learning activities.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	( )	( )	( )	( )	( )	strongly agree

66. **The instructor was helpful in identifying areas of agreement and disagreement on course topics that helped me to learn.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	( )	( )	( )	( )	( )	strongly agree

67. **I felt comfortable conversing through the online medium.** *
Mark only one oval.

	1	2	3	4	5	
strongly disagree	( )	( )	( )	( )	( )	strongly agree

☐ Send me a copy of my responses.

Appendix D

Semi-Structured Interview Protocol

IRB #: 843443-5

1) Tell me a little about your educational goals and why you decided to take this course online rather than in the classroom.

2) How did you achieve success in this course? How did you get through the difficult parts?

3) What skills or abilities do you think a student needs to pass an online course?

4) What is the role of the student in an online class? Is it the same or different than in the classroom?

5) What role did the instructor play in helping you succeed in this course?

6) How did other students in your online course affect your experience?

7) While taking this course, what other obligations competed for your time? How did you manage everything you needed to do?

8) Describe the support your family or friends provided while you were taking this course. What part do you think family support plays in student success?

9) What role did student services at the university play in your success? Are there other services you wish had been available to you while you were taking this course?

10) If you were redesigning this course, how would you improve it?

11) If you were giving advice to another student about how to succeed in an online course, what would you say?

12) Is there anything else you'd like to tell me about your success in this course?

Appendix E

Predictive Models

Logistic regression was used to create a predictive model of success for each level of class standing. Table E.1 presents a composite list of variables from all seven predictive models, along with the possible values for each variable. An asterisk depicts the reference value identified for each variable, as used in logistic regression analyses.

Table E.1 List of values for variables used in predictive models. An asterisk indicates reference values.

Independent Variable	Measure	Values
AGE	Ordinal	Under 20* 20-24 25-29 30-39 40-49 50 and over
ATHLETE	Dichotomous	No* Yes
CLASS SIZE	Ordinal	Less than 15* 15-30 31-45 46-60 More than 60
CUM GPA	Ordinal	0.00 to 0.99* 1.00 to 1.99 2.00 to 2.99 3.00 to 3.99 4
DEGREE LEVEL	Nominal	Occupational Endorsement* Certificate Associate Bachelors Post-bac/Licensure Masters Ph.D.
eLEARNING COURSES ONLY	Dichotomous	No* Yes
FEMALE	Dichotomous	No* Yes
FINANCIAL AID	Nominal	No Aid* Need-based Aid Non-need-based Aid
FIRST-TIME eLEARNING	Dichotomous	No* Yes
FULL-TIME STUDENT	Dichotomous	No* Yes
LOCATION	Nominal	AK Urban* AK Suburban AK City AK Rural Outside Alaska
RACE	Nominal	Unknown Asian Black Hi/Pac Islander Native/Indian White*

Non-degree Students

The model generated for non-degree-seeking students (Equation E.1) predicted 12.9% of variance (null –2LL = 3219.533, χ^2 = 821.221, p <.001). Logistic regression output is shown in Table E.2.

Table E.2 Logistic regression results for non-degree-seeking students.

	B	SE	Wald	df	p	Odds Ratio
CUM GPA			553.902	4	.000	
CUM GPA 1.00-1.99	.601	.195	9.512	1	.002	1.824
CUM GPA 2.00-2.99	1.884	.184	105.105	1	.000	6.579
CUM GPA 3.00-3.99	3.090	.182	288.939	1	.000	21.988
CUM GPA 4	3.705	.230	260.001	1	.000	40.645
RACE			20.060	5	.001	
RACE UNKNOWN	-.233	.128	3.332	1	.068	.792
RACE ASIAN	-.342	.302	1.275	1	.259	.711
RACE BLACK	-.797	.321	6.177	1	.013	.451
RACE HAWAIIAN/PAC ISLAND	-.587	.496	1.403	1	.236	.556
RACE NATIVE/INDIAN	-.536	.142	14.338	1	.000	.585
FEMALE	.249	.105	5.631	1	.018	1.282
FIRST-TIME eLEARNING	.436	.105	17.264	1	.000	1.547
eLEARNING COURSES ONLY	.295	.106	7.732	1	.005	1.343
Constant	-1.841	.210	76.953	1	.000	.159

The resulting model for non-degree-seeking students is:

$$\text{Logit}(\hat{Y}) = -1.841 + 0.601\,X_1 + 1.884\,X_2 + 3.090\,X_3 + 3.705\,X_4 - 0.233\,X_5 - 0.342\,X_6 - 0.797\,X_7 - 0.587\,X_8 - 0.536\,X_9 + 0.249\,X_{10} + 0.436\,X_{11} + 0.233\,X_{12} \quad \text{(E.1)}$$

Where $\hat{Y}$ is SUCCESS,

X_1 is the count of students with cumulative GPA falling into the category of 1.00-1.99

X_2 is the count of students with cumulative GPA falling into the category of 2.00-2.99

X_3 is the count of students with cumulative GPA falling into the category of 3.00-3.99

X_4 is the count of students with cumulative GPA of 4.00

X_5 is the count of students of unknown race

X_6 is the count of students who self-identified their race as Asian

X_7 is the count of students who self-identified their race as Black

X_8 is the count of students who self-identified their race as Hawaiian/Pacific Islander

X_9 is the count of students who self-identified their race as Native/Indian

X_{10} is the count of female students

X_{11} is the count of students taking an eLearning course for the first time

X_{12} is the count of students taking eLearning courses exclusively

First-time Freshmen

Equation E.2 displays the predictive model for success among first-time freshmen. This model increased accurate classification from 64.8% to 82.6%, predicting 17.8% of variance (null –2LL = 1388.605, $\chi^2 = 550.962$, $p < .001$). Logistic regression output is displayed in Table E.3.

Table E.3 Logistic regression results for first-time freshmen.

	B	SE	Wald	df	p	Odds Ratio
CUM GPA			256.330	4	.000	
CUM GPA 1.00-1.99	2.286	.429	27.155	1	.002	9.840
CUM GPA 2.00-2.99	3.681	.411	80.410	1	.000	39.705
CUM GPA 3.00-3.99	5.292	.422	157.058	1	.000	198.829
CUM GPA 4	5.838	.538	117.799	1	.000	343.058
FULL-TIME STUDENT	.454	.180	6.340	1	.012	1.575
LOCATION			10.693	4	.030	
LOCATION ALASKA SUBURBAN	.209	.225	.860	1	.354	1.232
LOCATION ALASKA CITY	-.366	.316	1.339	1	.247	.693
LOCATION ALASKA RURAL	-.621	.277	5.046	1	.025	.537
LOCATION OUTSIDE ALASKA	.346	.321	1.165	1	.280	1.413
Constant	-3.318	.408	66.250	1	.000	.036

The resulting model for first-time freshmen is:

$$\text{Logit}(\hat{Y}) = -3.318 + 2.286\,X_1 + 3.681\,X_2 + 5.292\,X_3 \qquad \text{(E.2)}$$

$$+\,5.838\,X_4 + 0.454\,X_5 - 0.209\,X_6 - 0.366\,X_7 - 0.621\,X_8$$

$$+\,0.346\,X_9$$

Where $\hat{Y}$ is SUCCESS,

X_1 is the count of students with cumulative GPA falling into the category of 1.00-1.99

X_2 is the count of students with cumulative GPA falling into the category of 2.00-2.99

X_3 is the count of students with cumulative GPA falling into the category of 3.00-3.99

X_4 is the count of students with cumulative GPA of 4.00

X_5 is the count of full-time students

X_6 is the count of students located in Alaska suburbs

X_7 is the count of students located in Alaska cities

X_8 is the count of students located in rural Alaska

X_9 is the count of students located outside Alaska

Continuing Freshmen

The model generated for other freshmen (not first-time), shown in Equation E.3, predicted 13.6% of variance, increasing accurate classification from 62.7% to 76.3% (null –2LL = 5429.550, χ^2 = 1450.929, p <.001). Output from the logistic regression analysis is shown in Table E.4.

Table E.4 Logistic regression results for continuing freshmen.

	B	SE	Wald	df	p	Odds Ratio
CUM GPA			825.525	4	.000	
CUM GPA 1.00-1.99	1.843	.325	32.083	1	.000	6.317
CUM GPA 2.00-2.99	3.318	.314	111.847	1	.000	27.595
CUM GPA 3.00-3.99	4.923	.318	239.810	1	.000	137.406
CUM GPA 4	5.726	.395	210.010	1	.000	306.710
RACE			22.458	5	.001	
RACE UNKNOWN	-.022	.088	.065	1	.799	.978
RACE ASIAN	.451	.387	1.361	1	.243	1.570
RACE BLACK	-.236	.227	1.087	1	.297	.790
RACE HAWAIIAN/PAC ISLAND	-.611	.453	1.820	1	.177	.543
RACE NATIVE/INDIAN	-.495	.121	16.781	1	.000	.610
ATHLETE	1.080	.290	13.838	1	.000	2.945
CLASS SIZE			16.538	4	.002	
CLASS SIZE 15–30	.461	.139	10.921	1	.001	1.585
CLASS SIZE 31–45	.390	.150	6.731	1	.009	1.478
CLASS SIZE 46–60	.373	.185	4.047	1	.044	1.452
CLASS SIZE MORE THAN 60	.773	.204	14.405	1	.000	2.165
FEMALE	.214	.089	5.715	1	.017	1.238
DEGREE LEVEL			9.674	3	.022	
DEGREE LEVEL CERTIFICATE	-.088	.360	.060	1	.806	.916
DEGREE LEVEL ASSOCIATE	-.300	.346	.751	1	.386	.741
DEGREE LEVEL BACHELORS	-.040	.351	.013	1	.909	.961
Constant	-3.389	.480	49.902	1	.000	.034

The resulting model for continuing freshmen students is:

$$\text{Logit}(\hat{Y}) = -3.389 + 1.843\,X_1 + 3.318\,X_2 + 4.923\,X_3 \tag{E.3}$$

$$+\,5.726\,X_4 - 0.022\,X_5 + 0.451\,X_6 - 0.236\,X_7 - 0.611\,X_8$$

$$-\,0.495\,X_9 + 1.080\,X_{10} + 0.461\,X_{11} + 0.390\,X_{12} + 0.373\,X_{13}$$

$$+\,0.773\,X_{14} + 0.214\,X_{15} + 0.088\,X_{16} + 0.300\,X_{17} + 0.040\,X_{18}$$

Where $\hat{Y}$ is SUCCESS,

X_1 is the count of students with cumulative GPA falling into the category of 1.00-1.99

X_2 is the count of students with cumulative GPA falling into the category of 2.00-2.99

X_3 is the count of students with cumulative GPA falling into the category of 3.00-3.99

X_4 is the count of students with cumulative GPA of 4.00

X_5 is the count of students of unknown race

X_6 is the count of students who self-identified their race as Asian

X_7 is the count of students who self-identified their race as Black

X_8 is the count of students who self-identified their race as Hawaiian/Pacific Islander

X_9 is the count of students who self-identified their race as Native/Indian

X_{10} is the count of UA Athletes

X_{11} is the count of students in a course with 15-30 students

X_{12} is the count of students in a course with 31-45 students

X_{13} is the count of students in a course with 46-60 students

X_{14} is the count of students in a course with more than 60 students

X_{15} is the count of female students

X_{16} is the count of students admitted to a certificate-level degree program

X_{17} is the count of students admitted to an associate-level degree program

X_{18} is the count of students admitted to a bachelor-level degree program

Sophomores

The model generated for sophomores (Equation E.4) increased accurate classification from 73.9% to 78.0% (null –2LL = 6082.679, χ^2 = 1116.100, $p < .001$).

Table E.5 Logistic regression results for sophomore students.

	B	SE	Wald	df	p	Odds Ratio
CUM GPA			740.599	4	.000	
CUM GPA 1.00-1.99	.307	.340	.815	1	.367	1.359
CUM GPA 2.00-2.99	2.182	.310	49.442	1	.000	8.865
CUM GPA 3.00-3.99	3.695	.313	139.196	1	.000	40.245
CUM GPA 4	5.634	.659	73.071	1	.000	279.798
RACE			16.869	5	.005	
RACE UNKNOWN	-.077	.082	.891	1	.345	.925
RACE ASIAN	.483	.337	2.048	1	.152	1.621
RACE BLACK	-.200	.200	1.001	1	.317	.819
RACE HAWAIIAN/PAC ISLAND	.184	.420	.193	1	.661	1.203
RACE NATIVE/INDIAN	-.365	.101	13.175	1	.000	.694
ATHLETE	1.375	.272	25.555	1	.000	3.954
CLASS SIZE			12.262	4	.016	
CLASS SIZE 15–30	.188	.114	2.710	1	.100	1.207
CLASS SIZE 31–45	.317	.123	6.578	1	.010	1.373
CLASS SIZE 46–60	.407	.165	6.083	1	.014	1.502
CLASS SIZE MORE THAN 60	.454	.155	8.576	1	.003	1.574
DEGREE LEVEL			12.000	3	.007	
DEGREE LEVEL CERTIFICATE	-1.599	1.158	1.908	1	.167	.202
DEGREE LEVEL ASSOCIATE	-1.783	1.151	2.400	1	.121	.168
DEGREE LEVEL BACHELORS	-1.971	1.150	2.937	1	.087	.139
Constant	.017	1.168	.000	1	.988	1.017

The resulting model for sophomore students is:

$$\text{Logit}(\hat{Y}) = 0.017 + 0.307\,X_1 + 2.182\,X_2 + 3.695\,X_3 \qquad \text{(E.4)}$$

$$+ 5.634\,X_4 - 0.077\,X_5 + 0.483\,X_6 - .200\,X_7 + 0.184\,X_8$$

$$- 0.365\,X_9 + 1.375\,X_{10} + 0.188\,X_{11} + 0.317\,X_{12} + 0.407\,X_{13}$$

$$+ 0.454\,X_{14} - 1.599\,X_{15} - 1.783\,X_{16} - 1.971\,X_{17}$$

Where $\hat{Y}$ is SUCCESS,

X_1 is the count of students with cumulative GPA falling into the category of 1.00-1.99

X_2 is the count of students with cumulative GPA falling into the category of 2.00-2.99

X_3 is the count of students with cumulative GPA falling into the category of 3.00-3.99

X_4 is the count of students with cumulative GPA of 4.00

X_5 is the count of students of unknown race

X_6 is the count of students who self-identified their race as Asian

X_7 is the count of students who self-identified their race as Black

X_8 is the count of students who self-identified their race as Hawaiian/Pacific Islander

X_9 is the count of students who self-identified their race as Native/Indian

X_{10} is the count of UA Athletes

X_{11} is the count of students in a course with 15-30 students

X_{12} is the count of students in a course with 31-45 students

X_{13} is the count of students in a course with 46-60 students

X_{14} is the count of students in a course with more than 60 students

X_{15} is the count of students admitted to a certificate-level degree program

X_{16} is the count of students admitted to an associate-level degree program

X_{17} is the count of students admitted to a bachelor-level degree program

Juniors

Equation E.5 displays the predictive model for success among junior students. This model predicted 2.7% of variance (null –2LL = 5979.806, $\chi 2$ = 985.594, p <.001).

Table E.6 Logistic regression results for junior students.

	B	SE	Wald	df	p	Odds Ratio
CUM GPA			539.590	4	.000	
CUM GPA 1.00-1.99	1.926	.749	6.615	1	.010	6.862
CUM GPA 2.00-2.99	3.711	.725	26.168	1	.000	40.093
CUM GPA 3.00-3.99	5.094	.726	49.189	1	.000	163.045
CUM GPA 4	5.706	.776	54.110	1	.000	300.694
RACE			73.793	5	.000	
RACE UNKNOWN	.097	.090	1.163	1	.281	1.102
RACE ASIAN	.064	.243	.068	1	.794	1.066
RACE BLACK	-.161	.184	.764	1	.382	.851
RACE HAWAIIAN/PAC ISLAND	-1.681	.337	24.889	1	.000	.186
RACE NATIVE/INDIAN	-.617	.095	41.885	1	.000	.540
ATHLETE	.960	.230	17.353	1	.000	2.611
FINANCIAL AID			13.513	2	.001	
FINANCIAL AID NEED-BASED	-.254	.083	9.430	1	.002	.776
FINANCIAL AID NON-NEED-BASED	.061	.093	.430	1	.512	1.063
AGE			30.678	5	.000	
AGE 20-24	-1.000	.288	12.064	1	.001	.368
AGE 25-29	-1.089	.296	13.515	1	.000	.337
AGE 30-39	-1.227	.295	17.355	1	.000	.293
AGE 40-49	-1.514	.312	23.508	1	.000	.220
AGE 50 AND OVER	-1.164	.366	10.106	1	.001	.312
FEMALE	.347	.078	19.632	1	.000	1.414
Constant	-2.238	.782	8.182	1	.004	.107

The resulting model for sophomore students is:

$$\text{Logit}(\hat{Y}) = -2.238 + 1.926\,X_1 + 3.711\,X_2 + 5.094\,X_3 \tag{E.5}$$

$$+\,5.706\,X_4 + 0.097\,X_5 + 0.064\,X_6 - 0.161\,X_7 - 1.681\,X_8$$

$$-\,0.617\,X_9 + 0.960\,X_{10} - 0.254\,X_{11} + 0.061\,X_{12} - 1.000\,X_{13}$$

$$-\,1.089\,X_{14} - 1.227\,X_{15} - 1.514\,X_{16} - 1.164\,X_{17} + 0.347\,X_{18}$$

Where $\hat{Y}$ is SUCCESS,

X_1 is the count of students with cumulative GPA falling into the category of 1.00-1.99

X_2 is the count of students with cumulative GPA falling into the category of 2.00-2.99

X_3 is the count of students with cumulative GPA falling into the category of 3.00-3.99

X_4 is the count of students with cumulative GPA of 4.00

X_5 is the count of students of unknown race

X_6 is the count of students who self-identified their race as Asian

X_7 is the count of students who self-identified their race as Black

X_8 is the count of students who self-identified their race as Hawaiian/Pacific Islander

X_9 is the count of students who self-identified their race as Native/Indian

X_{10} is the count of UA Athletes

X_{11} is the count of students who received need-based financial aid

X_{12} is the count of students who received non-need-based financial aid

X_{13} is the count of students falling into the age category of 20-24

X_{14} is the count of students falling into the age category of 25-29

X_{15} is the count of students falling into the age category of 30-39

X_{16} is the count of students falling into the age category of 40-49

X_{17} is the count of students falling into the age category of 50 and older

X_{18} is the count of female students

Seniors

Equation E.6 displays the predictive model for success among senior students (null –2LL = 7949.841, $\chi 2$ = 1072.813, p <.001). Logistic regression output is provided in Table E.7.

Table E.7 Logistic regression results for senior students.

	B	SE	Wald	df	p	Odds Ratio
CUM GPA			669.249	4	.000	
CUM GPA 1.00-1.99	1.088	.485	5.042	1	.025	2.970
CUM GPA 2.00-2.99	2.758	.446	38.166	1	.000	15.770
CUM GPA 3.00-3.99	4.106	.446	84.595	1	.000	60.713
CUM GPA 4	4.817	.516	87.013	1	.000	123.583
RACE			17.473	5	.004	
RACE UNKNOWN	.104	.081	1.633	1	.201	1.110
RACE ASIAN	-.117	.182	.417	1	.518	.889
RACE BLACK	.184	.157	1.378	1	.240	1.202
RACE HAWAIIAN/PAC ISLAND	-.507	.367	1.911	1	.167	.602
RACE NATIVE/INDIAN	-.290	.093	9.747	1	.002	.748
FINANCIAL AID			8.509	2	.014	
FINANCIAL AID NEED-BASED	-.105	.072	2.116	1	.146	.901
FINANCIAL AID NON-NEED-BASED	.152	.084	3.257	1	.071	1.164
AGE			30.841	5	.000	
AGE 20-24	.636	.523	1.481	1	.224	1.890
AGE 25-29	.336	.525	.411	1	.522	1.400
AGE 30-39	.206	.525	.154	1	.695	1.229
AGE 40-49	.380	.530	.513	1	.474	1.462
AGE 50 AND OVER	.547	.541	1.020	1	.312	1.728
FEMALE	.341	.063	28.876	1	.000	1.406

Table E.7 continued

	B	SE	Wald	df	p	Odds Ratio
FIRST-TIME eLEARNING	.248	.080	9.578	1	.002	1.282
eLEARNING COURSES ONLY	-.155	.072	4.686	1	.030	.856
FULL-TIME STUDENT	.248	.070	12.492	1	.000	1.282
LOCATION			21.472	4	.000	
LOCATION ALASKA SUBURBAN	.261	.092	8.012	1	.005	1.298
LOCATION ALASKA CITY	.406	.124	10.745	1	.001	1.501
LOCATION ALASKA RURAL	-.177	.136	1.699	1	.192	.838
LOCATION OUTSIDE ALASKA	.167	.103	2.622	1	.105	1.182
CLASS SIZE			14.902	4	.005	
CLASS SIZE 15–30	-.006	.091	.004	1	.947	.994
CLASS SIZE 31–45	.193	.097	3.922	1	.048	1.212
CLASS SIZE 46–60	.282	.124	5.163	1	.023	1.325
CLASS SIZE MORE THAN 60	.302	.164	3.378	1	.066	1.352
Constant	-3.074	.697	19.430	1	.000	.046

The resulting model for senior students is:

$$\begin{aligned}\text{Logit}(\hat{Y}) &= -3.074 + 1.088\,X_1 + 2.758\,X_2 + 4.106\,X_3 \\ &+ 4.817\,X_4 + 0.104\,X_5 - 0.117\,X_6 + 0.184\,X_7 - 0.507\,X_8 \\ &- 0.290\,X_9 - 0.105\,X_{10} + 0.152\,X_{11} + 0.636\,X_{12} + 0.336\,X_{13} \\ &+ 0.206\,X_{14} + 0.380\,X_{15} + 0.547\,X_{16} + 0.341\,X_{17} + 0.248\,X_{18} \\ &- 0.155\,X_{19} + 0.248\,X_{20} + 0.261\,X_{21} + 0.406\,X_{22} - 0.177\,X_{23} \\ &- 0.167\,X_{24} - 0.006\,X_{25} + 0.193\,X_{26} + 0.282\,X_{27} + 0.302\,X_{28}\end{aligned} \quad \text{(E.6)}$$

Where $\hat{Y}$ is SUCCESS,

X_1 is the count of students with cumulative GPA falling into the category of 1.00-1.99

X_2 is the count of students with cumulative GPA falling into the category of 2.00-2.99

X_3 is the count of students with cumulative GPA falling into the category of 3.00-3.99

X_4 is the count of students with cumulative GPA of 4.00

X_5 is the count of students of unknown race

X_6 is the count of students who self-identified their race as Asian

X_7 is the count of students who self-identified their race as Black

X_8 is the count of students who self-identified their race as Hawaiian/Pacific Islander

X_9 is the count of students who self-identified their race as Native/Indian

X_{10} is the count of students who received need-based financial aid

X_{11} is the count of students who received non-need-based financial aid

X_{12} is the count of students falling into the age category of 20-24

X_{13} is the count of students falling into the age category of 25-29

X_{14} is the count of students falling into the age category of 30-39

X_{15} is the count of students falling into the age category of 40-49

X_{16} is the count of students falling into the age category of 50 and older

X_{17} is the count of female students

X_{18} is the count of students taking an eLearning course for the first time

X_{19} is the count of students taking eLearning courses exclusively

X_{20} is the count of full-time students

X_{21} is the count of students located in Alaska suburbs

X_{22} is the count of students located in Alaska cities

X_{23} is the count of students located in rural Alaska

X_{24} is the count of students located outside Alaska

X_{25} is the count of students in a course with 15-30 students

X_{26} is the count of students in a course with 31-45 students

X_{27} is the count of students in a course with 46-60 students

X_{28} is the count of students in a course with more than 60 students

Graduate Students

The model generated for graduate students is shown in Equation E.7. Logistic regression output is displayed in Table E.8 (null –2LL = 566.085, $\chi^2 = 44.527$, $p < .001$).

Table E.8 Logistic regression results for graduate students.

	B	SE	Wald	df	p	Odds Ratio
AGE*			17.127	4	.002	
AGE 25-29	-1.262	.638	3.909	1	.048	.283
AGE 30-39	-1.530	.618	6.134	1	.013	.217
AGE 40-49	-.993	.671	2.188	1	.139	.370
AGE 50 AND OVER	-2.189	.642	11.640	1	.001	.112
LOCATION			10.143	4	.038	
LOCATION ALASKA SUBURBAN	.484	.420	1.322	1	.250	1.623
LOCATION ALASKA CITY	1.072	.539	3.955	1	.047	2.920
LOCATION ALASKA RURAL	1.796	.735	5.975	1	.015	6.023
LOCATION OUTSIDE ALASKA	.170	.386	.192	1	.661	1.185
FULL-TIME STUDENT	.943	.280	11.325	1	.001	2.569
Constant	3.271	.603	29.373	1	.000	26.332

* Because there were no graduate students under the age of 20, the reference value for the variable of age was 20-25.

The resulting model for graduate students is:

$$\text{Logit}(\hat{Y}) = 3.271 - 1.262\,X_1 - 1.530\,X_2 - 0.993\,X_3 \qquad \text{(E.7)}$$

$$- 2.189\,X_4 + 0.484\,X_5 + 1.072\,X_6 + 1.796\,X_7 + 0.170\,X_8$$

$$- 0.943\,X_9$$

Where $\hat{Y}$ is SUCCESS,

X_1 is the count of students falling into the age category of 25-29

X_2 is the count of students falling into the age category of 30-39

X_3 is the count of students falling into the age category of 40-49

X_4 is the count of students falling into the age category of 50 and older

X_5 is the count of students located in Alaska suburbs

X_6 is the count of students located in Alaska cities

X_7 is the count of students located in rural Alaska

X_8 is the count of students located outside Alaska

X_9 is the count of full-time students