USING LEARNING ANALYTICS TO PREDICT ACADEMIC SUCCESS IN ONLINE AND FACE-TO-FACE LEARNING ENVIRONMENTS

by

Lisa Janine Berry

A dissertation

submitted in partial fulfillment

of the requirements for the degree of

Doctor of Education in Educational Technology

Boise State University

May 2017

DEFENSE COMMITTEE AND FINAL READING APPROVALS

of the dissertation submitted by

Lisa Janine Berry

Dissertation Title: Using Learning Analytics to Predict Academic Success in Online and Face-To-Face Learning Environments

Date of Final Oral Examination: 06 March 2017

The following individuals read and discussed the dissertation submitted by student Lisa Janine Berry, and they evaluated the student's presentation and response to questions during the final oral examination. They found that the student passed the final oral examination.

Jui-long Hung (Andy), Ed.D.	Chair, Supervisory Committee
Kerry Lynn Rice, Ed.D.	Member, Supervisory Committee
Jesůs Trespalacios, Ph.D.	Member, Supervisory Committee

The final reading approval of the dissertation was granted by Jui-long Hung (Andy), Ed.D., Chair of the Supervisory Committee. The dissertation was approved by the Graduate College.

ABSTRACT

This learning analytics study looked at the various student characteristics of all on-campus students who were enrolled in 100 and 200 level courses that were offered in both online and face-to-face formats during a two-year period. There is a perception that online education is either not as successful as face-to-face instruction, or it is more difficult for students. The results of this study show this is not the case.

The goal of this study was to complete an in-depth analysis of student profiles addressing a variety of demographic categories as well as several academic and course related variables to reveal any patterns for student success in either online or face-to-face courses as measured by final grade. There were large enough differences within different demographic and academic categories to be considered significant for the study population, but overwhelmingly, the most significant predictor of success was found to be past educational success, as reflected in a student's cumulative grade point average.

Further analysis was completed on students who declared high school credit as their primary major based on significantly different levels of success. These students were concurrent enrollment students or those who completed college courses for both high school and university credit. Since most of these students were new to the university, they did not have a cumulative GPA, so other predictive factors were explored. The study concludes with recommendations for action based on the logistic regression prediction tool that resulted from the data analysis.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE: INTRODUCTION

Background

Students across the United States are choosing to continue their education beyond high school at an increasing rate. In 2012, approximately 41% of the population of 18-24-year-olds were enrolled in an institution of higher education (National Center for Education Statistics, 2014b). Ten years earlier only 36% of 18-24-year-olds opted to enroll in college. Online learning is growing at an even faster rate than overall enrollments. In 2014, about 28% of post-secondary students were enrolled in at least one distance learning course (Allen & Seaman, 2016; Hart, 2012). In contrast, in 2002, less than 10% of students opted for distance learning.

The university that was the basis of this study experienced growth in the overall student population as well as online course enrollments. The fall 2014 enrollment was approximately 29,100 students, nearly a 20% increase from just ten years earlier. Of these students, about 11,400, or 39%, were enrolled in at least one online course. Following the national trend, the university saw a 13% decrease in the number of students enrolled in exclusively face-to-face courses over the past two years (eCampus Center, 2015).

Problem Statement

Despite the growth in higher education enrollments, both online and face-to-face, retention of students until a degree is earned is a concern. Retention is defined as an institution's ability to retain a student from either admission to graduation, or from one term to the next (Berger & Lyon, 2005). Retention rates are calculated by determining the percentage of students who reenroll in the university for the next term. Nationally, the retention rate of full-time students from year to year is 71.8%, but when students are enrolled only part-time, the retention rate drops to 42.2% (National Center for Educational Statistics, 2014a). The university that was the focus of this study saw significant growth in year-to-year retention of full-time students, both face-to-face and online, over the past ten years. This number grew from 58.6% in 2002 to 71.7% in 2012, which is very close to the national average (Office of Institutional Research, 2013).

Persistence is a term that is often used in relation to retention. Retention is measured from the perspective of the university, while persistence is reenrollment or the desire to reenroll from the student's point of view. Students make decisions about whether to persist in their education based on a number of factors. Researchers established a number of theories on why students persist in their education starting in the 1970s (Astin, 1975; Bean & Metnzer, 1985; Spady, 1970; Tinto, 1975). These theoretical frameworks consider how the needs of the individual student align with what the institution offers to students. Astin (1975) proposed that students enter the university system with their unique set of inputs, including demographics, high school grades, and reasons for wanting to attend college, among many others. It is the interaction between the inputs and the higher education environment that determine the educational outcome. Additionally, Tinto (1975) proposed an interactional theory of retention. His theory suggested that there are multiple interrelated reasons as to why a student might not persist in their education. The studies completed by Astin and Tinto both address the person who enters the university system and how their personal characteristics and past experiences can impact their education success. This framework served as the foundation for this study. In addition to the factors described in the persistence theories, academic factors can influence a student's decision as to whether to persist in their education.

One of the key organizational factors is convenience. If educational options are convenient for students, they are more likely to persist throughout the term and enroll in coursework during the next term. Most university level students complete their post-secondary education in a traditional manner, on a college campus in a classroom. This model works well for most traditional students, who choose to live on campus or are local commuter students. However, the option to enroll in courses at a distance has expanded opportunities for many students, especially those defined as nontraditional. Nontraditional students are those that meet one or more of these categories: students that are enrolled on a part-time basis, work more than 35 hours per week while enrolled in coursework, are financially independent, have dependents or are a single parent, do not have a high school diploma, or delayed beginning their higher education for a period of time after high school (Watt & Wagner, 2016).

With the convenience of online course offerings, students can be located anywhere in the world and successfully complete their school work. Courses offered online are taken by students in remote locations as well as by students who reside on campus. This option provides flexibility for even local students, giving them the option to work on coursework as their schedule allows as opposed to one determined by the university. Nationally, 14% of higher education students were enrolled in some, but not all, distance education classes (Allen & Seaman, 2016). This same statistic is much higher in the state that is the location of this study, with 24.6% of students enrolled in at least some distance education classes (National Center for Educational Statistics, 2014b).

If students report taking only some of their higher education courses online, then the remainder of their classes must be completed on campus.

While the online delivery model provides convenience for both time and location, it has caused concern about the quality of the courses as compared to the more traditional, face-to-face, delivery model (Patterson & McFadden, 2009). These concerns are based on a review of pass rates that compare face-to-face and online learning. Ideally, the two delivery models, face-to-face and online, provide equal opportunities for students, and in turn, have a consistent rate of reenrollment the next term. Clark (1983) reviewed literature addressing media comparison studies from as early as the 1960s. He concluded that, when considering learning outcomes as the sole measure of comparison, well-designed studies show no significant difference in knowledge gained from one medium to another. Thus, when comparing face-to-face and online versions of the same course, learning outcomes should be the same (Lockee, Burton, & Cross, 1999). Clark argued that differences in achievement, or persistence during a course, are due to some other influence. These influences may include the instructional methods (Clark, 1983), student motivation, self-discipline (Colorado & Eberle, 2010), student post-secondary readiness, or cultural factors (Braxton & Hirschy, 2005).

Whatever the reason, if a student does not progress in their education, meaning they do not receive a grade that allows them to continue in their course work, they are much more likely to dropout or stopout of their education (Habley, Bloom, Robbins, & Gore, 2012; Ishler & Upcraft, 2004). A dropout is when a student ceases their enrollment in the university, and a stopout is when a student stops their enrollment in the university for a period of a semester or more, but then returns to continue their education. Both dropouts and stopouts can be initiated by the student, or by the institution. If the institution does not allow reenrollment, it is typically due to lack of an acceptable academic progress or a violation of school code of conduct.

Patterson and McFadden (2009) completed a study analyzing demographic data of students doing poorly in both face-to-face and online delivery models and found a higher dropout rate in the online environment. Age was a factor in persistence, with older students being more likely to dropout. Another study found that females are more successful than males in completing courses in the online environment (Aragon & Johnson, 2008). Considering these findings, this study aimed to identify these and other student characteristics that lead to more successful outcomes in one delivery model over another. The range of student characteristics included demographic as well as academic and course specific data that was both static and dynamic.

Despite the perception that students do worse in online courses as compared to face-to-face, leadership at the university has invested significant funds and resources to encourage the growth of online learning for both on-campus and remote students. Continued growth of online learning is an essential component of the university's strategic plan. One of the goals of the strategic plan is to "facilitate the timely attainment of educational goals for our diverse student population" (Office of the Provost, 2012). This goal pushes all students to continuously attend the university until they earn the desired degree or certificate. One strategy included in the plan to help attain this goal is to use technology and multiple delivery formats to provide options for students. To help meet the goals outlined in the strategic plan, it is important to predict if students with a specific set of characteristics are more likely to be successful in either an online delivery model or a face-to-face format. It will be beneficial to have knowledge about success in specific courses as well as courses offered by specific departments. This knowledge can be used to inform student advising sessions, or to guide recommendations for course registration. The information can also help university leadership make decisions about which departments or courses may be due for a curriculum evaluation. In addition, individual courses, either online or face-to-face, may be identified for a redesign, or the information can be used to guide decisions for expansion of programs or degree offerings for either face-to-face or online formats. At a broader level, this information can be used to guide both the recruiting and admissions processes (Kalsbeek & Zucker, 2013).

Between 2000 and 2012, retention between the first and second year of enrollment for students both first time and transfer students, increased by over 10% at the university that is the focus of this study (Office of Institutional Research, 2013). This indicates progress toward reaching the goal outlined in the university's strategic plan. Although there has been overall growth in both retention and graduation rates between 2000 and 2012, there was not consistent growth (Office of Institutional Research, 2013). This presented a need for an analysis of demographic and academic data over multiple years to address variances in persistence rates and to identify trends over more recent years. Since the university will benefit from having increased retention and graduation rates, it will be advantageous for the leadership to be informed on the characteristics of successful students in both online and face-to-face course delivery modes.

Purpose of Study

Students may fail to persist in post-secondary education due to gaps in their expectations as compared to their educational experience, a lack of academic aptitude and skill, or for economic reasons (Braxton & Hirschy, 2005). The purpose of this study was to identify what types of students were more successful face-to-face and which were more successful online. Some students enter college and successfully earn a degree, while others end up leaving their chosen institution for a variety of reasons. This study examined some of the characteristics that were common to students who were successful in both of these course delivery modes.

The significance of this study is to provide information to university stakeholders about trends in academic success and who persisted in their education whether the student opted for online or face-to-face course modalities. Stakeholders can use the information gleaned from this study to inform decisions related to policymaking and academic advising. Additionally, the information can be used to identify retention issues and curricular concerns. Students can use academic trends identified through this type of learning analytics to reflect and self-select course enrollment options.

Academic success can be defined in a number of ways. For the purposes of this study, a grade of C- or better is deemed as successful because this is the grade required for any prerequisite courses across the university. Additionally, it is the same measure used by Liu, Gomez, and Yen (2009) in their study on retention and final grades.

Universities, as well as individual students, can benefit from persistent enrollment until a degree is attained (Baum, Ma, & Payea, 2013). They are often compared by measures such as graduation rate and retention rate (Adelman, 1999). These statistics can be used as a recruiting tool for both students and faculty. In addition to monetary benefits for the university, individuals can benefit from staying in school until a degree or certificate is obtained. Students are more likely to be employed, earn more pay, and, once employed, they are more likely to receive additional compensation beyond a salary such as pension and health benefits (Baum, et al., 2013; U.S. Bureau of Labor Statistics, 2015).

If institutions of higher education are informed of which types of students persist, particularly in a specific course modality, university personnel may be better prepared to counsel students who do not have similar characteristics toward success or offer additional support to certain students. This quantitative study examined a variety of student demographic characteristics including age, gender, ethnicity, as well as several academic factors including current university grade point average (GPA), enrollment status, and year in school. A correlational analysis was used to determine any patterns of success for on-campus students in either face-to-face or online classes. This was followed by a series of logistic regression analyses which were completed in order to identify predictors of success. Following the correlation and regression analyses, a deeper analysis of courses from an outlier area was completed in an attempt to identify the underlying reasons for some of the educational trends.

Research Questions

This study addressed demographic, academic, and course related factors of on-campus students and analyzed their success rates in 100 and 200 level courses taken either online or face-to-face at a university in the west. Only enrollments in courses that were offered in both formats between the Fall 2013 semester and the Summer 2015 semester were included in the data analysis. These factors led to the following research questions:

1. Which are important predictors from student characteristic profiles that lead to successful completion of 100 and 200 level classes taken online, as measured by final grade?
2. Which are important predictors from student characteristic profiles that lead to successful completion of 100 and 200 level classes taken face-to-face, as measured by final grade?
3. What predictors are common or differ between online and face-to-face settings?
4. Which academic departments or individual courses can be identified as significant and in need of further analysis?

CHAPTER 2: LITERATURE REVIEW

Introduction

This chapter addresses literature relevant to the study. The first section reviews the emphasis of retention and graduation rates for both face-to-face and online as higher education has evolved over time in the United States. Later sections address retention theories and factors that affect persistence as well as factors that affect student achievement. The next section discusses some of the differences between online and face-to-face course delivery models, and the final section reviews how learning analytics and data mining have been used to explore student success.

Evolution of Retention Tracking in Higher Education

Origins of Higher Education and Distance Learning

Institutions of higher education were established in the United States long before the country was founded. Many of the early institutions were founded with religious freedom in mind. Their goal was to provide religious education for future ministers (Geiger, 2015; Snyder, 1993). At that time, the focus of the universities was to facilitate the spread of religion as opposed to retention of students, so records of this nature were not kept.

In the early nineteenth century, traditional four-year universities expanded their curriculum, shifting beyond religious studies to a focus on the classical topics such as classical languages, ethics, philosophy, and the sciences (Berger & Lyon, 2005; Snyder, 1993). Also during this time, American higher education began to include normal schools, two-year institutions designed to prepare teachers for the public school system. Enrollment in higher education during the nineteenth century was very exclusive. Enrollment across the country consisted of only 1% of people 18 to 24 years of age (Snyder, 1993). Because of the elite status for university level students, retention was not perceived as an issue and therefore was not tracked (Berger & Lyon, 2005).

The first evidence of distance education was found in Europe during the same time higher education in the United States was in its early expansion. As early as the mid-1800s, students in Great Britain were learning shorthand through courses offered via the postal service. Language classes were offered in both France and Germany using a similar approach. Learning through correspondence began in the United States a few decades later (Colorado & Eberle, 2010; Moore & Kearsley, 2005). These courses had a goal of spreading knowledge, so retention was still not a consideration.

The 1930s – 1960s

The beginning of the twentieth century brought the expansion of industrialism, which, in turn, caused an increase in demand for a more highly educated workforce (Berger & Lyon, 2005). This need enabled universities to either grow or become more selective in who was accepted as a student based on the institutional goals. Universities with increased enrollments, particularly those that were less selective in who was accepted, began to track retention of students. The first report on retention was released in 1938 (Berger & Lyon, 2005). This report, entitled *College Student Mortality*, examined dropout rates at several universities in the 1930s. It considered the time it took students to complete a degree as well as the impact of several student factors including gender, age, work status, living arrangements, and location of home as compared to university location. During this time, some innovative institutions implemented distance education employing mail based correspondence courses as well as delivery of higher education courses over radio broadcasts (Colorado & Eberle, 2010; Moore & Kearsley, 2005).

Major world events during this time frame had an impact on enrollment trends at the higher education level. World War II had a significant effect on enrollments since societal efforts were focused on the war as opposed to getting an education. As a result, college enrollments dropped 20% between the 1939-1940 and 1943-1944 school years (Snyder, 1993). Male students were a much higher portion of the group that departed college as compared to females. However, once the war was over, enrollment numbers grew quickly. This growth is partially due to the GI Bill that was passed by congress in 1944 to provide incentives for veterans of the war to take advantage of higher education opportunities (Bean & Metzner, 1985; Bok, 2013).

To encourage ongoing education, the United States Armed Forces founded a distance learning institute around the time of the beginning of World War II. This military based organization offered both high school and college level courses to members of the military (Moore & Kearsley, 2005). There were opportunities for correspondence courses, telephone based education, and courses offered via television. These models allowed people to continue their education wherever they were located.

The launch of Sputnik, in 1957, initiated another surge in post-secondary enrollments. This event helped to create the mindset that getting a higher education would help strengthen the United States as a whole. Soon after the Higher Education Act was passed, in 1965, providing grants and low-interest loans to help students pay for their education (Bean & Metzner, 1985; Berger & Lyon, 2005; Bok, 2013). This surge transitioned enrollment in institutions of higher education from the elite to commonplace, leading to a more diverse student body (Berger & Lyon, 2005; Bok, 2013). This growth also brought students to the university system who lacked the proper preparation to be successful. Students did not know what to expect either academically or socially, and colleges were not prepared to provide that information to students. As a result, the more diverse student audience brought an increase in dropouts (Berger & Lyon, 2005).

The 1970s – 1980s

The enrollment surge of the 1960s created an increased interest in tracking enrollment, student persistence, and satisfaction with the educational experience (Berger & Lyon, 2005). Two major studies completed in the 1970s examined college dropouts and a variety of factors that may have contributed to students leaving the higher education system. Spady (1970) looked at environmental factors, while Kamens (1971) compared dropout rates to the size and prestige of the institution. These studies determined that there were higher dropout rates at larger institutions. The large institutional experience was less personal because students had fewer opportunities to get to know the faculty teaching their courses (Kamens, 1971). He also found that students who attended a university that was perceived as more prestigious regarded their education as having more value thereby making them more employable. Studies like those completed by Spady (1970) and Kamens (1971) led institutions to be more strategic in their enrollment practices. Universities worked to select students with more academic and social preparedness, specifically students with research and writing practice, which were more likely to graduate (Berger & Lyon, 2005).

During this time, another organization that led the implementation of alternative education modalities was the Electronic University Network, a consortium consisting of several post-secondary institutions. By the 1980s, the Electronic University Network had over two hundred television based courses available to learners across the United States, most were available on public broadcasting stations (Moore & Kearsley, 2005). These courses were some of the early attempts to provide expanded flexibility for learners.

The 1990s – Today

As higher education transitioned into the twenty-first century, retention rates were still lower than desired. Dropouts ranged from a low of 8% at private elite institutions to a high of 50% at open enrollment colleges (Berger, & Lyon, 2005). Before this time, most institutions were single mode institutions, offering only one mode of instruction. Advances in technology caused many institutions to begin exploring new instructional models. Some expanded to operating as dual mode institutions, offering two modes of instruction, most often face-to-face and distance learning options. Still other institutions had individual faculty members who opted to move their courses online. Most institutions, offering a mix of face-to-face and online course modalities, were created with the forethought of a sustainable model, however, when a single faculty member chooses to move their course online without institutional support, they often do not endure (Moore & Kearsley, 2005). Many institutions of higher education found expansion to include alternate instructional delivery models, including a variety of distance learning models, allowed for continued growth in enrollments without sacrificing the existing student population. This expansion also continued to grow the diversity of the student audience (Berger & Lyon, 2005).

In an attempt to provide even more opportunities for students, some educators worked to provide distance learning incorporating a variety of media options. Courses used a combination of correspondence and media including video, via live broadcasting or video recordings, audio, printed study guides, with assignments submitted via mail (Colorado & Eberle, 2010; Moore & Kearsley, 2005). Another multimedia course delivery model implemented during the late twentieth century was teleconferencing. Teleconferencing used either one-way or two-way communication using video (Moore & Kearsley, 2005).

The next phase of distance learning was centered on the use of computers and the Internet (Colorado & Eberle, 2010; Moore & Kearsley, 2005). Use of this technology allowed for a multimedia experience combining the use of text, graphics, audio, and video in the learning experience. The phrase online learning is synonymous with distance learning via the Internet. Early iterations of online learning were not much more than correspondence courses that used email in place of postal mail.

Online learning became much more feasible and more widely adopted with the advent of the learning management system (LMS). Learning management systems and their improvements came in three waves. Early learning management systems provided a structured environment for sending and receiving documents. The arrival of Web 2.0 tools enhanced online learning and learning management systems by providing opportunities for students to interact with the content in real time. The next, and most recent, significant change in online learning came with combining the field of data analytics used in business and industry with the learning management systems in learning analytics (Brown, 2011).

Factors Impacting Persistence

As early as the 1970s researchers developed theoretical frameworks to explain student retention or lack thereof (Astin, 1975; Bean & Metzner, 1985; Spady, 1970; Tinto, 1975). Many early persistence frameworks were based on a suicide theory. These theories worked under the assumption that a combination of academic and social integration into the environment was critical to thriving. If the student felt they did not fit in, either academically or socially, then they were at risk of dropping out or ending their life at the institution (Spady, 1970; Tinto, 1975). Because of the era in which these theories were created, they were focused on face-to-face students. However, they can be transferred to all instructional models.

Astin (1975) attempted to explain persistence using an Input-Environment-Outcome model. He theorized that students enter higher education with a number of foundational characteristics, or inputs, that influence their ability to persist. The input variables include demographic characteristics, high school grades, and reasons for wanting to attend college, as well as many other factors. Astin also identified a number of environmental variables that were likely to affect the likelihood of success for students. Environmental factors included variables related to the institution, like size and location of the university; factors related to the faculty, including teaching methodologies and values; and characteristics related to the student, including the type of residence, the level of extracurricular involvement, academic major, and peer group factors. Astin considered the output variables the results of the environmental variables on the input variables (Ishler & Upcraft, 2004). The outcome variables include satisfaction with the environment, academic achievement, and retention.

Tinto (1975) expanded Spady's theory, which focused on multiple reasons why a person might not persist in their education, to propose an interactional theory of college departure. The theory is labeled as interactional because there are often multiple interrelated reasons why a student chooses to leave school. Astin's and Tinto's theories intersect at the point that they both consider the set of characteristics that a student has when beginning their higher education experience (Ishler & Upcraft, 2004). Tinto's theory includes both sociological and psychological reasons for students to drop out or stop out of their education (Braxton & Hirschy, 2005). Bean and Metzner (1985) added organizational reasons to the theories for lack of persistence. All of the persistence theories address primarily voluntary dropout or stopouts as opposed to students who do not reenroll for reasons determined by the institution (Berger & Lyon, 2005; Ishler & Upcraft, 2004). The institution may deny reenrollment due to serious misconduct or consistent failing grades. Voluntary departure most often occurs when a student feels the obstacles to success are insurmountable.

Sociological Factors

Sociological reasons for persistence are related to the degree to which a student recognizes the value of their education in relation to their career goals (Habley et al., 2012). In conflict, lack of student retention may occur when students feel like they do not fit into a university due to differences between their culture of origin and the culture of the university (Braxton & Hirschy, 2005). Students may be influenced by pressures for a certain level of academic performance, and if they are unable to achieve that expectation, they could opt to withdraw from school. This issue can be minimized if institutions and courses emphasize building a community. This often results in higher levels of student satisfaction, and consequently, a higher rate of retention (Lotsari, Verykios, Panagiotakopoulos, & Kalles, 2014). Student engagement, whether behavioral, emotional, or cognitive, is positively correlated with student achievement (Adelman, 1999; Pardo, 2014), so is an essential component of sociological satisfaction with the educational experience.

Psychological Factors

Psychological factors that affect persistence can be either internal or external. Internal factors that can influence persistence include academic success, motivation, self-esteem issues, and study habits. Student motivation and perception of learning can also affect their persistence in school. Some students are only looking for surface level learning, meaning they simply want to pass the test and get a grade. These students may get less out of their educational experience than those looking for a deeper level of learning. These students are looking to relate new information to previous knowledge, find patterns in the content, and gain a deep understanding of the underlying principles (Stansfield, McLellan, & Connolly, 2004).

External factors can also influence a student's decision to stay in school. These factors include family issues, time constraints like employment demands, as well as the perceived level of support and encouragement from family, friends, and coworkers (Bean & Metzner, 1985; Park & Choi, 2009; Tello, 2007). External factors are likely to be more prevalent in nontraditional students, particularly those who need to balance family, work, and school aspects of life. These are the same factors that often cause students to choose online courses as opposed to face-to-face options (Pontes, Hasit, Pontes, Lewis, & Siefring, 2010).

Organizational Factors

Bean and Metzner (1985) were the first to consider retention from an organizational perspective as opposed to that of the student. Universities have a vested interest in getting students to stay in school until a degree is earned. Persistence requires students to conform to the organizational norms of the institution, but the institution plays a key role in this conformity (Habley et al., 2012).

Students must have the proper academic aptitude and skill along with personality traits that allow them to integrate themselves into the college environment (Braxton & Hirschy, 2005; Park & Choi, 2009). If a student does not fit into the organizational norms of the institution, it can affect their level of satisfaction with the university. Tinto (1975) found that students needed to adapt to the routine of the institution. They need to learn how to participate and communicate to fit into the college environment both inside and outside of the classroom. This adaptation is dependent on the structure of the university as well as the flexibility of the student. If this integration does not take place, a student is much more likely to drop out of the institution. These learning communities exist in both the face-to-face and online learning environments. Institutions can encourage opportunities to ease student adaptation to the organization through the use of student orientation, learning communities, appropriate academic advising, and other support services (Ishler & Upcraft, 2004; Swail, 2004).

Often orientation activities are a student’s first exposure to the higher education environment. Students should be introduced to the essential policies and procedures, as well as the learning communities that they will become a part of as they move forward in their education. Academic advising should take place in conjunction with the orientation, setting the student down the proper path to academic success (Ishler & Upcraft, 2004).

<u>Economic Factors</u>

While not included in the theories established in the 1970s, current-day students also consider economic reasons for persistence in institutions of higher education (Braxton and Hirschy, 2005). The current average cost of tuition, fees, room and board for a full-time undergraduate student is approximately $20,000 per year. About 84% of full-time undergraduate students rely on financial aid in the form of grants, loans, work-study, or other sources to help cover these costs (National Center for Educational Statistics, 2015). Many students struggle to see the return on investment of time, money, and effort put into their education, thus select other career options that do not require further education. The time spent working to pay back loans can also be a deterrent to continuing in school until a degree is attained. On the other hand, financial aid can provide opportunities for some highly motivated students who might not otherwise be able to access higher education (Swail, 2004).

Another economic factor that can affect students is the state of the economy. A poor economy can mean fewer jobs are available, motivating unemployed people to return to school to further their education, in hopes of becoming more employable. In contrast, when the economy is thriving, students may choose to stopout of school in favor of a job. On the other hand, a strong economy may push students to be more successful in their coursework, in the hopes that there are jobs waiting for them once they graduate (Berger & Lyon, 2005).

Factors Impacting Student Achievement

Poor academic achievement is second only to financial reasons for the lack of student persistence in higher education (Bean, 2005). Academic achievement can be measured by grade point average (GPA), test scores, class rank, or final course grades. In addition to academic achievement, demographic, and cultural factors, the structure of the courses a student chooses and the level of student self-regulation can influence how a student does in school, and in turn, affect the likelihood of a student persisting until degree completion. All of these factors contribute to a student's set of entry characteristics. Table 1 provides a summary compilation of several key student predictors and the study reporting the data.

Academic Factors

Class status is one of the top academic predictors of success in both face-to-face and online courses. The longer a student has been in school, the more likely he or she is to complete a degree (Hart, 2012; Levy, 2007; Moore & Kearsley, 2005; Wang & Newlin, 2002). Several studies found grade point average (GPA) to be positively correlated with success in individual courses (Aragon & Johnson, 2008; Campbell, DeBlois, & Oblinger, 2007; Dupin-Bryant, 2004; Harrell & Bower, 2011; Hart, 2012; Jayaprakash, Moody, Laura, Regan, & Baron, 2014; Menager-Beeley, 2001; Morris, Wu, & Finnegan, 2005; Muse, 2003; Osborn, 2001; Shelton, Hung, & Baughman, 2015; Valasek, 2001). Some of these studies also found that both the verbal and mathematic scores on the SAT are strong predictors of academic success (Campbell et al., 2007; Cortes, 2013; Morris et al., 2005). McKenzie and Schweitzer (2001) reported academic

Table 1 Predictors of Retention for Various Student Characteristics

Student Characteristic	Relationship of Characteristic to Academic Retention	Studies Addressing Characteristic
Academic Advising and Support	More support is positively correlated with persistence	Swail (2004) Face-to-Face Only: Adelman (1999); Thayer (2000) Online Only: Ivankova & Slick (2007)
Academic Level/ Year in School *	The further in school is a positive predictor for online course success	Online Only: Dupin-Bryant (2004); Levy (2007); Muse (2003); Osborn (2001)
Academic Load/ Number of Credits *	More credits correlate to more likely to be successful	Campbell et al.(2007) Online Only: Colorado & Eberle (2010)
Academic Readiness/ High School Rigor	More college preparation correlates to more success	Choy (2001); Demetriou & Schmitz-Sciborski (2011);Nora & Crisp (2012) Face-to-Face Only: Adelman (1999) Online Only: Aragon & Johnson (2008), Müller (2008); Muse (2003);
Age *	Younger students are more successful	Nora & Crisp (2012) Online Only: Hung, Hsu, & Rice (2012); Menager-Beeley (2001); Osborn (2001); Yasmin (2013)
	Older students are more successful	Online Only: Muse (2003); Valasek (2001)

* Variable included in this study.

Student Characteristic	Relationship of Characteristic to Academic Retention	Studies Addressing Characteristic
Course Subject *	Students are more successful in some subject areas. Math tends to be more challenging.	Online Only: Hung et al. (2012); Yasmin (2013)
Entrance Exam Scores *	Higher test scores are a positive predictor	Campbell et al. (2007); Cortes (2013); Reason (2003) Online Only: Morris et al. (2005)
Ethnicity *	Asians and Caucasians more likely to persist	Nora & Crisp (2012); Reason, 2003; Swail (2004)
	Blacks, Hispanics, Native Americans less likely to persist	Bowen, Chingos, & McPherson (2009); Nora & Crisp (2012); Reason (2003); Swail (2004)
Financial Aid Eligibility	Lower socioeconomic status students are less likely to persist	Campbell et al.(2007); Swail (2004)
	Higher socioeconomic status students are more likely to persist	Bowen et al. (2009); Swail (2004)
First Generation Student *	First-generation students are less likely to be successful	Choy (2001); Falcon (2015); Stebleton & Soria (2013) Face-to-Face Only: Thayer (2000)
Gender *	Females are more successful	Online Only: Aragon & Johnson (2008); Hung et al. (2012); Yasmin (2013)
	Males are more likely to persist	Online Only: Tello (2007)

* Variable included in this study.

Student Characteristic	Relationship of Characteristic to Academic Retention	Studies Addressing Characteristic
Grade Point Average (GPA) *	Higher GPA correlates to higher success online	Bowen et al. (2009); Campbell et al.(2007); Devadoss & Foltz (1996); Reason (2003); Swail (2004) Face-to-Face Only: Adelman (1999) Online Only: Aragon & Johnson (2008); Dupin-Bryant (2004); Harrell & Bower (2011); Menager-Beeley (2001); Morris et al. (2005); Muse (2003); Osborn (2001); Valasek (2001)
High School GPA *	Higher GPA a positive predictor of academic success	Bowen et al. (2009); Cortes (2013); Nora & Crisp (2012); Reason (2003) Online Only: Morris et al. (2005)
Major *	Some majors do better than others, undeclared majors are less likely to persist	Campbell et al.(2007) Online Only: Tello (2007)
Parent Education Level	Higher parent education level is positively associated with persistence	Choy (2001)
Self-Efficacy	More self-efficacy a student has the more likely they are to be successful	Cortes (2013); Demetriou & Schmitz-Sciborski (2011) Online Only: Holder (2007); Ivankova & Stick (2007); Kemp (2002); Müller (2008)

* Variable included in this study.

Student Characteristic	Relationship of Characteristic to Academic Retention	Studies Addressing Characteristic
Self-Motivation	Motivated students tend to be successful	Demetriou & Schmitz-Sciborski (2011); Devadoss & Foltz (1996); Nora & Crisp (2012) Face-to-Face Only: Adelman (1999) Online Only: Ivankova & Stick (2007); Liu, Gomez, & Yen (2009); Muse (2003); Valasek (2001)
Student Age Similar to Peers	Positive effect	de Freitas et al. (2015)
Student Attendance	Attendance in face-to-face classes is a positive predictor of success	Devadoss & Foltz (1996)
Student Engagement	More social interaction with faculty or other students is a positive predictor of academic success	Demetriou & Schmitz-Sciborski (2011); de Freitas et al. (2015); Nora & Crisp (2012); Swail (2004) Face-to-Face Only: Thayer (2000) Online Only: Hung et al. (2012); Ivankova & Stick (2007); Liu et al. (2009); Müller (2008); Valasek (2001)
Support of Family and Friends	More support correlates with more persistence	Choy (2001); Swail (2004) Face-to-Face Only: Adelman (1999) Online Only: Holder (2007); Müller (2008); Osborn (2001); Park & Choi (2009)
Work Commitments	Students who are employed are less likely to persist to graduation	Kemp (2002); Tello (2007); Yasmin (2012)

* Variable included in this study.

success on a more general level finding that academic performance in higher education mirrors that of previous academic experiences. This correlation is true for both students with good grades as well as those who were unsuccessful (Lee & Choi, 2011). Students who enter a post-secondary institution less prepared for the academic rigor tend to struggle academically. This causes students to take longer to graduate (Ishler & Upcraft, 2004). Additionally, the more time that has passed since a student last took a class, the more likely they are to struggle when reenrolling (Colorado & Eberle, 2010; Moore & Kearsley, 2005). In contrast to these weaknesses, students who enter a course knowing how to study are more likely to be successful (Moore & Kearsley, 2005; McKenzie & Schweitzer, 2001). In addition to studying, students who make attendance in their classes a priority perform better (Devadoss & Foltz, 1996).

Demographic Factors

Early attempts at online learning were promoted as if all diversity could be hidden in an online environment (Rovai, Ponton, & Baker, 2008). While this could never happen in a face-to-face classroom because of visual cues, this type of utopian environment may be possible online, although it is unlikely. In this type of class, the bias would be removed, but only until the instructor and students start interacting with each other. Students draw on their past experiences as learning resources, and these could not be shared without the diversity of the group being shared to some extent.

Males and females have different approaches to learning (Ewert, 2010; Rovai et al., 2008). Historically, males dominated the higher education student audience until the 1970s, when females surpassed males in the number of both enrollments and graduates (Ewert, 2010; Grebennikov & Skaines, 2009). Male students have a higher incidence of taking a break of a term or more while working on their post-secondary education. They are also more likely to attend school on a part-time basis (Ewert, 2010).

Rovai et al. (2008) found that, while enrolled in courses, males generally have a more positive attitude toward technology than their female counterparts. It may be due to this attitude toward technology that causes male students to exude more confidence in their online participation. Male students tend to use fewer qualifiers instead opting to use more intensifiers in their writing. When students are given the opportunity to interact with fellow students, females are more likely to ask questions while male students tend to answer questions more frequently. When working on low level learning tasks female students take notes and focus on absorbing the content where male students choose to ask questions directly to the instructor. In contrast, female students prefer interacting with fellow students when working on higher level learning tasks where males prefer independent processing. The same research added that female students use a “connected voice” when contributing to discussion forums, portraying empathy and the importance of relationships while male students use an “independent voice” which is more certain in its tone, and sometimes is interpreted as confrontational (Rovai et al., 2008). Overall studies show that females are more successful than males, although studies have varying results as to the significance of their findings (Ishler & Upcraft, 2004).

Age is another factor that is considered in the research on retention for the university population as a whole. Individual studies have differing results. Some studies have found younger students are more successful (Hung, Hsu, & Rice, 2012; Osborn, 2001; Yasmin, 2013), while others determined that older students do better in their coursework (Muse, 2003; Valasek, 2001). Older students are often classified as nontraditional students. The term nontraditional student refers to a student who meets one or more of the following characteristics: they are over the age of twenty-four, married, have children, or are financially independent (Ewert, 2010; Watt & Wagner, 2016). Any of these factors can have a detrimental effect on a student's attention to school work (Braxton & Hirschy, 2005; Park & Choi, 2009). It is these same factors that may cause a student to select online courses as opposed to face-to-face classes for the added flexibility that online options can offer.

Cultural and Societal Factors

Ethnicity is another demographic that is often used when considering success in higher education (Morris, n.d.; Richardson, 2012). Early researchers came up with theories based on genetics, hypothesizing that some races have more innate abilities than others. More recently, researchers argued that differences in educational outcomes are not due to genetics, but instead caused by the differences in economic, cultural, social, and historical circumstances. The nature versus nurture mentality spurred a new wave of research focused on educational interventions that aimed to overcome cultural differences (Morris, n.d.).

Modern research has centered on the cultural and societal factors that can have an effect on a student's predisposition toward education (Richardson, 2012). Hofstede (2001) defined a framework that can be used to compare cultures and how the societal factors may define how the culture views higher education. The framework uses five different scales or dimensions.

- Power – Distance Dimension. A measure of the disparity between those who have power and those who do not.

- Individualism – Collectivism Dimension. A scale that identifies how a person considers the effects of their actions.
- Uncertainty – Avoidance Dimension. A measure of how nervous people are in situations perceived as unstructured or unpredictable.
- Masculinity – Femininity Dimension. A range of how a culture identifies the distinction between what men are expected to do from what women are expected to do.
- Long-Term – Short-Term Orientation Dimension. A measure of the extent to which people from a society are looking toward the future as opposed to living in the present.

Cultural differences can affect how students interact with the instructor in courses, both face-to-face and online. If the students have a different cultural background than the instructor, it has the potential to affect student achievement. The student may be influenced by different comfort level on the power-distance dimension, and the role of the teacher; respecting their authority to the point that it hampers their success in the course (Rovai et al., 2008). Specifically, college level courses often incorporate the use of discussions. Discussions are frequently in the format of a debate where the intent is to have students debate the instructor and fellow students. The United States has a relatively low power-distance rating, however, students from cultures with a high power-distance rating may not feel comfortable challenging their instructor, a person in a place of authority (Sher, 2013). This could, in turn, adversely affect their grade, and in turn their overall academic success. Since minorities are a growing segment of the college population, it is important for university faculty and staff to have an awareness of cultural differences (Campbell et al., 2007).

Course Delivery Models

There is a spectrum of course delivery models ranging from a face-to-face classroom to a fully online course. One range within these delivery models is the amount of synchronous contact between instructor and student. Some classes take place in a fully synchronous format. This can occur in a classroom, via two-way video, or using a web-based meeting platform. Besides the level of synchronous contact, there are many considerations that can affect both the instructor and the student in these various course delivery models.

The roles of both the instructor and the student vary in the different course delivery methods. In face-to-face classes, the instructor often has the role of a "sage on the stage," or the subject matter expert standing in the front of the classroom distributing their knowledge to the students (King, 1993). This aligns with the traditional idea of an instructor lecturing while students are taking notes and attempting to absorb as much information as possible. This means the activities are often planned and led by the instructor (Stansfield et al., 2004).

In online courses, the instructor role often changes. They act more as a "guide on the side" (King 1993). Some instructors opt to play an active role in course facilitation, providing regular academic support for students as they work their way through the course content. Instructors grade assignments and provide feedback to students, as well as facilitate online discussion forums. They make themselves available to struggling students who ask for help. Other instructors take the initiative to contact students who seem to be struggling in their course. In this model, students have more control over their learning.

Malcolm Knowles (1984) identified a set of characteristics that are often preferred by adult learners. His learning theory is referred to as andragogy. Andragogy theory is based on a set of five assumptions regarding adult learners.

- Learner Control. Since adult learners are independent members of society, they prefer to have a similar level of control within the learning environment. Therefore they like opportunities where their learning is self-directed.
- Life Experience. Secondly, adult learners bring a vast array of experiences to the classroom. Knowles emphasized that these students learn best when they are encouraged to draw on their experiences and make connections between their past experience and the knowledge being gained through the educational experience.
- Need-Based Learning. Adult learners approach the learning situation cognitively and emotionally ready for the task at hand. Adults tend to choose to continue their education based on a perceived need. The need could be initiated by a career change or a family event.
- Value of Learning. Adult learners need a purpose for their learning. Toward this end, students need to be informed of the outcomes of the learning experience, and what value it will provide for them.
- Motivation to Learn. Finally, adult learners have an intrinsic motivation to learn (Knowles, 1984). This final assumption about these learners is very closely connected to the other assumptions. If a student is motivated to learn because it provides an opportunity for self-improvement, they are going to want to learn

information that is relevant to their lives, and information that provides opportunities to connect to prior experiences.

Another variable in different course delivery formats involves the amount of interaction among students (Stansfield et al., 2004). Some course formats, either online or face-to-face, allow students to work through the materials at their own pace in a relatively independent format. In this type of course, the student has opportunities to interact with the content and the teacher, but not fellow students. Other online courses are designed for a cohort of students. In these courses, students have the opportunity to interact with each other as well as with the content and the teacher. Either format requires students to be active participants. Asynchronous online courses provide the opportunity for students to think and reflect on the content prior to participating in class. Because of the nature of the discussions, there is the potential for more student interaction and participation than in a live classroom. Discussion activities in courses are in alignment with Knowles's andragogy theory because it provides an avenue for students to be able to draw on personal experiences and share them with others. This approach allows students to use each other as learning resources (Moore & Kearsley, 2005).

The instructor is responsible for building a sense of community within the course they teach (Rovai et al., 2008). In a face-to-face class, this can be accomplished through discussions and classroom activities. This is a relatively easy task when students are in a common location and time where students have all their senses gathering information in a similar environment. However, in an online course, without audio or video, the instructor and students do not have the visual cues of facial expressions, nor do they have the intonation cues available when listening to a conversation. Despite the lack of face-to-face contact, there can be other advantages to online learning. The increased opportunities for reflection, as well as unlimited access to the course content, provide a greater degree of learner control over the learning environment (Stansfield et al., 2004). The opportunity for reflection allows for deeper discussion as compared to those that take place in the face-to-face classroom. These discussions can be productive if students feel the online environment is a safe place for sharing their thoughts. In doing so, all participants, both instructors and students, need to have respect for diverse perspectives (Rovai et al., 2008).

One common concern related to multiple course delivery models is a perception of differences in course quality (Patterson & McFadden, 2009). To mitigate concerns, online and face-to-face versions of the same course should be developed around the same set of learning objectives. Both course models should have the same measurable course outcomes, although they may be achieved in different ways. If this is truly the case, the two course models should have similar measures of student success (Clark, 1983). When a study finds that student outcomes differ between face-to-face and online, those variances can typically be attributed to instructional strategies, student motivation, or self-discipline (Colorado & Eberle, 2010; Moore & Kearsley, 2005).

Learning Analytics

Analytics is the science of logical data analysis (Dziuban, Moskal, Cavanagh & Watts, 2012). The use of analytics is popular in business to predict customer choices. For example, many online shopping websites offer suggestions based on previous browsing on their site. Similar analytics of data can be applied in the field of education to predict student success or inform instructors on when and how to intervene with a student to reduced chances of failure, effectively allowing educators to gain similar benefits for students as businesses do for their customers through advertising (Martin & Sherin, 2013). The Society for Learning Analytics Research defines their field as “the measurement, collection, analysis and reporting of data about learners and their contexts for purposes of understanding and optimizing learning and the environment in which it occurs” (Siemens & Baker, 2012, pp. 1-2).

Learning analytics is often confused with the field of educational data mining. While the two fields have many similarities, some argue they evolved separately with a slightly different focus. The International Educational Data Mining Society defines educational data mining as “an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in” (Siemens & Baker, 2012, p. 1). Learning analytics focuses on data from the learner and their context that will be used to improve either the learning process or the learning environment. In contrast, educational data mining has a slightly broader approach. These researchers do not specify where their data originates, but they do stipulate that their goal is to better understand students and the various learning environments. The core difference between the two fields is that learning analytics incorporates human judgment, while educational data mining relies on computer automation (Baker & Siemens, 2014; Pardo, 2014; Siemens & Baker, 2012). This difference is evident in the discovery, analysis, and application of the data. For example, educational data mining researchers may apply their findings through having educational software automatically adapt to personalize learning experiences for users. In contrast, learning analytics results are used to inform instructors on how to assist struggling learners (Baker & Siemens, 2014).

Both learning analytics and educational data mining are emerging as new research fields because of the ever-increasing amount of data available (Baker & Siemens, 2014; Wagner & Ice, 2012). Stakeholders at all levels are expressing interest in access and use of the data including educators, institutions, government, and accrediting agencies. These groups are using the data to make decisions about instructional strategies, judgments on the quality of learning, student attrition and graduation rates, financial aid, and policies about online teaching and learning (Dringus, 2011). Jayaprakash et al. (2014) stated that "the goal of learning analytics is to uncover hidden patterns in educational data and use those patterns to attain a better understanding of the educational process, assess student learning, and make predictions on performance" (pp. 1-2). Researchers in learning analytics should focus on providing data that support student success as opposed to other goals such as maximizing profits for the university (Becker, 2013; Slade, & Prinsloo, 2013).

History of Learning Analytics

Using data to inform instruction is not new. On a small scale, teachers have used informal questioning and other formative assessment techniques in classrooms to gather information on student understanding for decades. Learning analytics in online learning became more formal when learning management systems first became available as opposed to individual websites for distance courses. Learning management systems were able to track data for users, both students and faculty (Picciano, 2012; Reyes, 2015). The second wave of data analysis came when Web 2.0 tools were incorporated into online learning situations (Brown, 2011). These tools provided additional data not available with learning management systems alone. The final wave of development for learning analytics and data mining came with the increased capacity to analyze large amounts of data. Learning managements systems and student information systems were linked to track vast amounts of data.

There is an ever increasing push for stakeholders to use big data in decision making. Globalization has pushed the demand for learning analytics by creating increased competition for online educational opportunities. Students no longer need to live in the same town as their chosen institution of higher education. Reduced public funding and increased government oversight have caused a need for institutions to show a return on investment for the education they provide to students (Lockyer, Heathcote, & Dawson, 2013; Picciano, 2012).

Learning Analytics Frameworks

Since the field of learning analytics is relatively new, there are only a few proposed models to provide structure for studies. Some of these models are based on older theories of knowledge development or the use of business intelligence (Elias, 2011). Each of these models originates from the definition of learning analytics in that they are designed to use available data to inform and improve teaching and learning.

Knowledge Continuum. In his dissertation, Baker (2007) proposed a theory on how businesses can make knowledge actionable. He expanded on an earlier theory, which proposed that information lies on a Knowledge Continuum based on the depth of how the data is used (Elias, 2011). Data is at the lowest level and used to answer “what is” questions. The next level higher is considered information. Information is used to answer questions about when and where. The third level on the spectrum is labeled as knowledge. Knowledge is used to answer questions about why and how. The high end of the knowledge spectrum is defined as wisdom. Information has achieved the wisdom level when it is applied to make improvements in the field.

Collective Applications Model. This model, proposed by Dron and Anderson (2009), defines a cyclical framework in which data is gathered, processed, and presented. Gathering data involves selecting and capturing the data. Processing the data involves aggregating and processing the data. Presenting the data includes determining how it is displayed. If the desired detail is not displayed, then the cycle is repeated with some level of change in what data goes through the process (Dron & Anderson, 2009; Elias, 2011).

The Five-Step Learning Analytics Process. Campbell and Oblinger (2007) proposed a five-stage model for learning analytics studies. The first stage is capturing the data. Researchers need to determine what data is needed, the level of granularity of the data, and how to retrieve that data (Campbell & Oblinger, 2007). During this stage, researchers should employ techniques to ensure the data is stored in a secure location (Pardo, 2014). Once the data is retrieved, the researcher must make decisions on how to organize the data prior to moving to the next stage of the process.

The second stage of the learning analytics process involves reporting on the data. The data needs to be processed in a manner that it can be summarized or combined for reporting in a usable format for the end user (Campbell & Oblinger, 2007; Pardo, 2014). During this stage, it is usually necessary to use statistics software tools that can handle large quantities of data. The tool selected depends on the type of data that was captured and the research questions to be considered (Greller & Drachsler, 2012). One critical component of the reporting stage is the development of a dashboard that is used to display the data in a meaningful way for stakeholders (Pardo, 2014). This stage includes computation of descriptive statistics for the data, which informs end users of what has happened in the past.

The next stage of the process is to make predictions based on the data and reporting completed in the previous stage. This involves answering questions that initiated the data capture in a manner that explains what is likely to happen. An accurate prediction depends on the use of a reliable model. This stage revolves around the generation of that model (Campbell & Oblinger, 2007).

Once a prediction is made, the next phase requires stakeholders to act on that prediction. If this stage is implemented correctly, actions will result in improvements (Pardo, 2014). These actions can be executed either manually or automatically. The number and type of interventions are based on the nature of the prediction that was made in the previous stage (Campbell & Oblinger, 2007). Depending on the type of reporting and predictions created during earlier stages of the learning analytics process, actions may be prescriptive in nature. Prescriptive actions should vary for different end users, or students, helping them to be successful.

The final stage of the learning analytics process is the refining stage. This is the stage of the process that makes this model unique. The models presented by Baker (2007) and Dron and Anderson (2009) do not define refining the data as a unique step in the process. Calling out the refinement of the data as a requirement of the process makes this model stronger than the other models described in the literature. Regular evaluation should take place on results of the actions taken during the act stage. In addition to evaluating the actions that take place, researchers should revisit the predictions used to determine those actions, the reporting that was used to predict, and even how the data was captured. Improvements could be made at any stage in the learning analytics process (Pardo, 2014).

Privacy and Ethics

There are potential ethical issues within the field of learning analytics. Primarily these are issues related to student privacy and ownership of the data (Reyes, 2015; Slade & Prinsloo, 2013). The Family Education Rights and Privacy Act (FERPA) is a federal law enacted to protect student privacy. This law guides institutions on how student data can be used for research, school improvement, and accountability, and when it is necessary to inform students (U.S. Department of Education, 2012). While some students may want to opt out of studies that involve learning analytics, it could change the interpretation of student learning in results of those studies in either a positive or a negative manner (Brown, 2011). Since this field is in its relative infancy, students need to be ensured that any learning analytics research used beyond the classroom and instructor has all personally identifiable information removed from the data prior to release to researchers (Oblinger, 2012).

One challenge related to learning analytics is that there are few guidelines or regulations in place to guarantee anonymity (Pardo, 2014; Reyes, 2015). Since there are minimal guidelines, researchers should be clear in defining the purpose of their study as well as how the sensitive data is being handled (Slade & Prinsloo, 2013).

Another ethical consideration is related to how the data are used once the analysis is completed. Data, especially personally identifiable data, should be used for research or school improvement reasons, whether predictive or prescriptive, as opposed to other reasons like making a profit (Slade & Prinsloo, 2013). At times, an in-depth analysis of data may lead to conclusions that can help stakeholders increase their understanding about student retention and academic success, but it may not be actionable data. Other instances provide information in which stakeholders can take immediate action. No matter how the data is used, there should be a balance between the push to gain knowledge against harming individuals, whether they are students or instructors (Slade & Prinsloo, 2013).

Since the results of data analysis have the potential to directly affect students and instructors, accurate interpretation of data is critical. If data are misinterpreted, there could be adverse effects. Students may become unmotivated, academic advising could be inaccurate, faculty members could lose opportunities for advancement, or the institution as a whole may lose enrollments. When acting on the data, stakeholders should keep in mind that the numbers that were analyzed represent real people. These people are part of the population, but may not have the same needs as the group (Slade & Prinsloo, 2013). An individual may be an exception to the norm or may have extenuating circumstances beyond what can be measured with the data alone, so it is essential to avoid profiling of students based on their demographic or academic characteristics. On the other hand, educators have an ethical obligation to act on the knowledge gained through the research (US Department of Education, 2012).

Uses of Data

The results from learning analytics studies are used by a variety of groups. How the data is used, and what actions are taken, depends on the needs of the group, and their placement in the hierarchy of the educational process (Jayaprakash et al., 2014; Shelton et al., 2015). Learning analytics data are used in three areas: descriptive, predictive, and prescriptive analyses (Affendey, Paris, Mustapha, Sulaiman, & Muda, 2010; Brown, 2011). Descriptive analysis helps create a portrait of past students, instructors, or other stakeholders, while predictive analysis predicts likely trends and outcomes for students prior to their experience (Affendey et al., 2010; Brown, 2011; Verbert, Manouselis, Drachsler, & Duval, 2012). Prescriptive analysis dictates interventions for various stakeholders within the educational community (Brown, 2011). Each of the user groups may use the data in a descriptive, predictive, or prescriptive manner based on their needs.

Higher Education Administrators. Higher education administrators use data analysis results in a variety of ways. Data are used to describe the student body as a whole as well as subpopulations within the university. Administrators can identify admissions prospects and predict the likelihood of their success (Dziuban et al, 2012). They detect retention issues, prescribe actions, and monitor graduation rates (Reyes, 2015). Administrators may also use data to identify issues in the learning community beyond the classroom itself that affect the success of students at the university (Pardo, 2014). Overall, the data reporting can lead to improved accountability across the university, leading to better use of resources, and an increased reputation, both within the university and beyond (Campbell & Oblinger, 2007).

University Staff. Learning analytics study results can be useful to instructional designers when creating online courses (Lockyer et al., 2013). Department level staff can use data to inform personnel decisions including teaching assignments and training needs (Berger & Lyon, 2005; Dziuban et al., 2012; Shelton et al., 2015). University staff that provides supplemental student resources benefits from learning analytics results to refine the timing and location of various services (Becker, 2013; Campbell & Oblinger, 2007).

Faculty. Both face-to-face and online faculty members can benefit from using data to inform their teaching. Data resulting from formative assessments can be used to identify knowledge gaps that can be addressed immediately in the classroom, positively helping current students (Reyes, 2015). Data from other sources, including the end of course evaluations along with LMS data, can be used in a prescriptive manner to inform adjustments to course content or pedagogy for future course offerings, particularly for online courses (Pardo, 2014). Learning analytics can encourage faculty members to take part in a self-reflection of their online teaching (Dringus, 2011). A self-reflection may encourage professional growth for faculty in the differences between face-to-face and online teaching and learning pedagogy (Shelton et al., 2015). Faculty members have the power to use learning analytics to guide students to success, affect practice, and contribute to the scholarship of teaching and learning (Campbell & Oblinger, 2007).

Students. Like faculty members, active students, as well as prospective students, should be able to take advantage of the large amounts of data automatically collected both prior to enrolling and while participating in online courses. Students may benefit from having access to predictive analysis results on given courses. This information should not be used to limit educational options, instead, it has the potential to inform their decisions on enrollment. Students can work with faculty on educational adjustments midcourse to improve their academic performance. Like faculty, students will benefit from data that encourage opportunities for self-reflection (Pardo, 2014). Reflection of this nature can affect progress in a current course, or inform decisions on future courses.

Student awareness of prescriptive analytics can lead to a more streamlined use of university resources (Campbell & Oblinger, 2007).

Government. Policy makers use data at all levels, descriptive, predictive, and prescriptive, to evaluate education on a national or regional level. The increase in learning analytics allows for new types of data use thereby expanding the ability to evaluate educational objectives. The new data can provide a different viewpoint for policy making decisions (Reyes, 2015).

Researchers. Researchers work with other stakeholders to share the information in a refined, usable format. Toward this end, researchers have a number of responsibilities. They are responsible for the validity and reliability of the data as it goes through the process of analysis and is shared with others (Reyes, 2015). Additionally, they are responsible for the de-identification of student data when details are reported beyond the classroom.

Summary of the Literature

Data has been used to inform instruction and track retention and graduation since the early years of higher education. Within the last decade, a dramatic increase in the data available has changed the way data is used in the decision-making process. Much of this is due to “big data” that is available in student information systems, learning management systems, and other longitudinal data systems. If this data is properly captured and reported, it can be used by a variety of stakeholders to predict or prescribe actions based on the data. There were a number of learning analytics models presented in the literature review, and each learning analytics study is driven by a model that allows the research to achieve maximum results. This study used the five-step process proposed by Campbell and Oblinger (2007) because it provided a framework that matched the focus of the study.

The decisions made based on the data are supported by the persistence theories established in the 1970s. These theories posited that the characteristics with which each student enters college, combined with the environment of the institution, can be used to identify reasons why a student may not succeed in their education. The review of the literature provided a comprehensive list of characteristics that were options for data collection points for this study. This study attempted to address as many of the variables listed in Table 1 as possible. However, one limitation of the purely quantitative study is that qualitative data is not available. As a result, those student characteristics included in Table 1 that are related to information about individual students or faculty choice were not available for this study. This included variables related to whether study participants accessed services offered by the university. Ultimately, this study addressed 50% of the student characteristics addressed in the literature. Those variables are indicated in Table 1 with an asterisk.

Finally, all of the literature reviewed for this study addressed the university population as a whole or focused on either the face-to-face or the online learning environments in isolation. This study addressed both face-to-face and online course enrollments separately as well as the population as a whole. This approach makes this study unique and allows the study to identify predictors that differ between the two audiences.

CHAPTER 3: METHODOLOGY

Overview

This study was centered on a detailed look at the data describing the on-campus students at a university in the western region of the United States who were enrolled in 100 and 200 level courses that were offered in both face-to-face and online formats over a two-year period. The results of this study can be used to inform academic advisors on whether students should choose to take a given course online or face-to-face. The results can also be used to identify courses and academic departments where students regularly have significantly different levels of performance, based on final grade, between the face-to-face and online versions.

Method

Campbell and Oblinger (2007) and Pardo (2014) described a process for learning analytics that includes five stages. This study adopted the five stage process of capture, report, predict, act, and refine. This process was used to address the following research questions:

1. Which are important predictors from student characteristic profiles that lead to successful completion of 100 and 200 level classes taken online, as measured by final grade?
2. Which are important predictors from student characteristic profiles that lead to successful completion of 100 and 200 level classes taken face-to-face, as measured by final grade?

3. What predictors are common or differ between online and face-to-face settings?
4. Which academic departments or individual courses can be identified as significant and in need of further analysis?

For the purposes of this study, completion of a course was considered successful if a student earned a grade of a C- or better. This definition was chosen because the university requires students to earn a C- or better in all prerequisite courses in undergraduate programs.

Participants

The data collected for this study was the entire population of on-campus students who were enrolled in the set of 100 and 200 courses that are offered in both online and face-to-face formats between the Fall 2013 semester and the Summer 2015 semester at the university. The collection of 100 and 200 level courses was selected because the university offers multiple sections of these courses in both formats every term. Blended courses were excluded from the study. Additionally, these courses have higher enrollments than many upper division courses, since they often function as service courses. Service courses are courses that are offered by one academic department but are required for many degrees or certificates. For example, anatomy and physiology is a course offered by the biology department but is required by degree programs ranging from kinesiology and nursing to criminal justice and social work.

Capture

The capture process involved three phases, as can be seen in Figure 1. First was the process of data collection, followed by organizing the data, then cleaning and validating the data.

Data Collection

Prior to data collection, an application was submitted to the Insitutional Review Board (IRB), and was approved. Data was exported from the data warehouse at the university where this study took place. The information was pulled from the PeopleSoft Student Information System database. PeopleSoft is the student information system adopted by the university. A detailed list of data points collected can be reviewed in Table 2.

To initiate the data collection process, a query was run to create a comprehensive listing of all 100 and 200 level core courses that are offered in both online and face-to-face formats. This list was used to determine which records to extract from the data warehouse. Courses offered in only one format or the other were excluded from this study. A number of courses were offered in other formats including hybrid or via teleconferencing, but those course sections were excluded from this study. Additional queries were run to gather demographic information as well as details on residency, first generation status, high school GPA, and entrance exam scores.

Once the data set was reduced, there were nearly 101,000 individual course enrollments for just over 23,800 students. Due to the large quantity of data, and the personal nature of the records, adherence to FERPA regulations was deliberate. The data was stored on a university computer, to insure the security of the data.

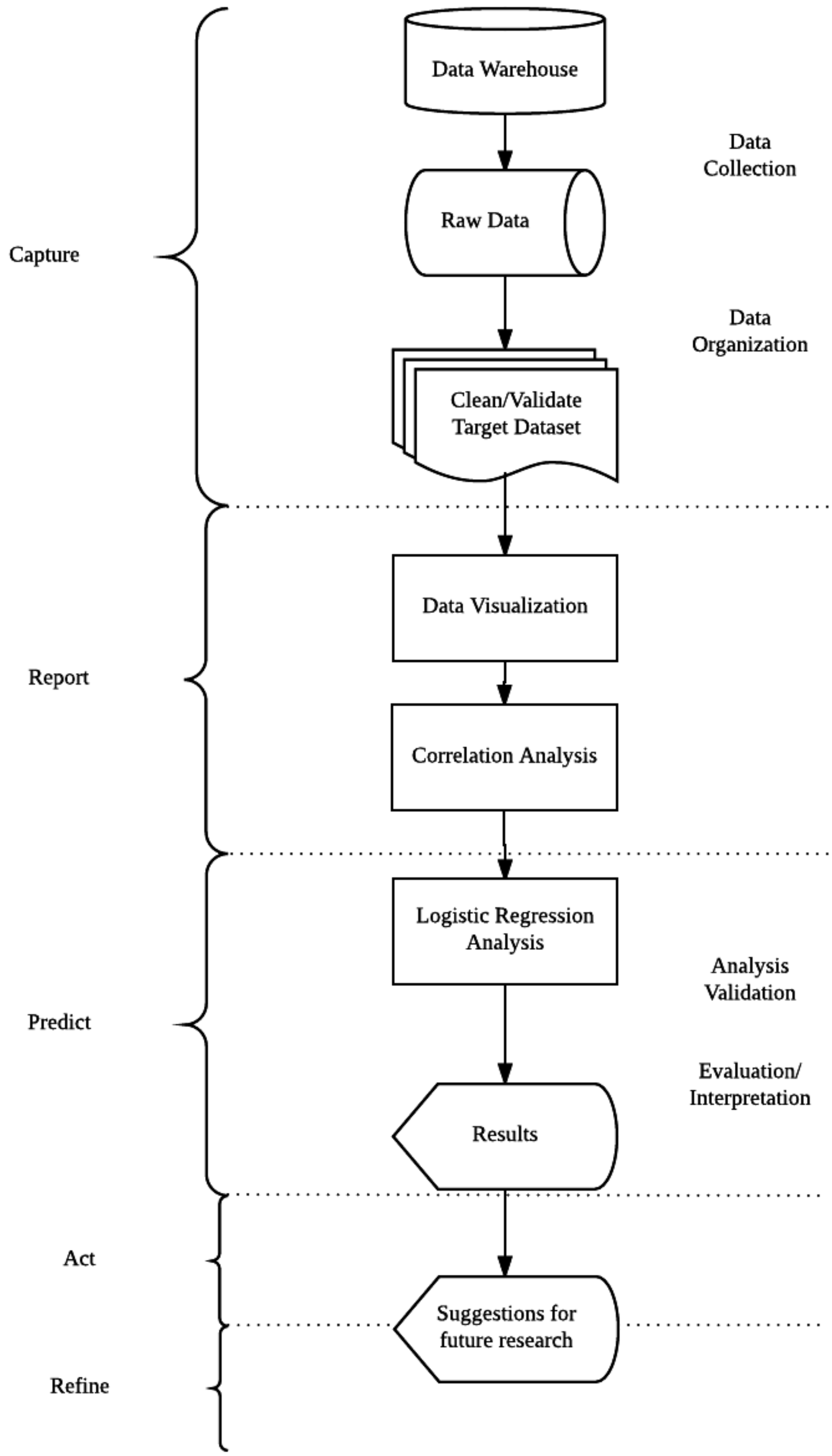


Figure 1 Visualization of Learning Analytics Process

Table 2 Data Variables

Variable Name	Variable Type
Academic Information	
Academic Level/Year in School	Nominal
Academic Load	Nominal
College Cumulative GPA	Continuous
Cumulative Credits Earned	Continuous
Degree Type	Nominal
Entrance exam scores (math, verbal, written, composite)	Discrete
Final Grade	Discrete
High School GPA	Continuous
Primary Major College	Nominal
Successful	Nominal
Term Enrolled	Nominal
Term GPA	Continuous
Withdrawal	Nominal
Course Information	
College	Nominal
Course Delivery Mode	Nominal/Binary
Course Code (i.e. ENG101)	Nominal
Course Level	Nominal/Binary
Course Section Enrollment	Continuous
Course Section Full	Nominal/Binary
Demographic Information	
Age at Time of Enrollment	Continuous
Age Category	Nominal
Declared Degree Count	Continuous
Declared Degree Type	Nominal
Ethnicity	Nominal
First Generation Student	Nominal/Binary
Gender	Nominal/Binary
Residential Status**	Nominal
Student ID*	Nominal

Note. All data is at time of course enrollment.
* A number used to identify multiple enrollments for a single student, not necessarily the university identification number.
** Indicates whether the student is a state resident.

Data Organization

Student identification numbers were included with the original data set. This information was used to join the data from multiple queries into a single merged data set. In an effort to maximize student privacy, the dataset was de-identified as soon as possible. De-identification of data is a process used to make the identification of individual students more difficult (Nelson, 2015; Slade & Prinsloo, 2013). Any personally identifiable information was encoded as soon as possible after data acquisition. This allowed the different enrollments for an individual student to be identified while minimizing the ability to identify his or her original student identification number. Each record collected was associated with a course enrollment. So, for example, if a single student was enrolled in three different 100 or 200 level courses, then there were three different records associated with that student. This approach allowed the study to account for all online course enrollments and all face-to-face course enrollments for courses included in the study. The data was delivered in a format that was easily imported into Microsoft Excel for data cleaning and then imported into SAS, a statistical software, for more in-depth analysis.

Data Cleaning and Validity

With a large data set, it is likely there will be invalid data (Hand, 1998). The dataset was evaluated, field by field, for any missing data points. Based on the nature of the data that was missing, many records were omitted from the study. For example, this occurred when details like the final grades were listed as incomplete or audit, or if the full-time status was not included. In some fields, a value of unknown was used (ethnicity), and in other fields, unknown values were left blank (entrance exam scores, residency information). Sorting and filtering strategies were used to identify anomalies in the data. For example, students with a GPA above a 4.0 were omitted from the dataset. The initial data set included all records for active enrollments as well as students who dropped the course prior to the course drop deadline. Since none of these records had a final grade associated with them, they were omitted from the study. Additionally, enrollments that were for a course that used a pass/fail grading format, courses for zero credits, enrollments that were audits of full courses and enrollments where a student received an incomplete were omitted from the study data set.

Some data required modification prior to analysis. One critical field was the reporting of final grades. Instructors at the university are given freedom in how they report final grades. Some issue only letter grades while others opt to use a +/- system. At some universities, a grade of C- is considered not passing, but that is not the case at the university where the study took place. For this study, a C- was considered passing. To minimize confusion in this field, all grades were truncated to consider only the letter grade. If a student withdrew from the course, their grade was considered equivalent to an F for statistical analysis. For calculation purposes, the standard 4.0 grade scale was used where an A was worth four points, a B was worth three points, a C was worth two points, a D was worth one point, and an F was worth zero points.

The year in school field was calculated based on the number of credits a student had completed based on the definition used by the university. A student is considered a freshman from initial enrollment through 25 credits earned, a sophomore when 26 to 57 credits have been earned, a junior when between 58 and 89 credits have been earned, a senior when 90 or more credits have been earned. Students who are pursuing a second baccalaureate degree or are graduate students were categorized separately.

Several of the variables were reduced for the logistic regression analysis. Reducing variables minimizes the number of different values for the variable. The individual course subjects were reduced from individual subjects to departments for initial analysis and then further reduced to the college offering the course for logistic regression analysis. A similar reduction of values was completed for the primary majors declared by the students. The degree type was reduced from eight different types of degrees or certificates to three values. It was important to distinguish students working toward a bachelor's degree, from those enrolled as college students while enrolled concurrently as high school students. All other degree types were grouped into a category labeled as other. Additionally, several variables were transformed to normalize the data distribution prior to the logistic regression analysis. These variables include the age at course start, the cumulative credits earned, the degree count, and the total enrolled in course.

Report

To report on the data, the analysis must be completed. For statistical testing, the independent, or outcome variable for this study was the course delivery model. This variable has two possible values, face-to-face and online. Two variables were used to measure success in each course enrollment. The final grade variable and a reduced version of the final grade that identified a course enrollment as successful or unsuccessful. An enrollment was identified as successful if the course enrollment resulted in a letter grade of an A, B, or C. Letter grades of D or F, as well as withdrawals, were labeled as unsuccessful course completion. All other variables were considered dependent, or predictor variables.

An initial analysis of the cleaned data was completed using descriptive statistics. This analysis provided an overall picture of the students who enroll in either online or face-to-face courses. The categorical variables were interpreted using percentages and graphs to describe the distribution of the population, while numerical data was described by reporting on the mean and standard deviation.

As can be observed in Figure 1, the reporting phase involved completing a detailed data visualization followed by a multivariate analysis involving a comprehensive set of correlational tests to identify which demographic, academic, and course related factors were related to student success in either online or face-to-face course enrollments. The correlation analysis was followed by a logistic regression analysis to create reports for the predict phase of the learning analytics process.

Predict

The results of the various analyses were used to create a prediction model. A comprehensive set of correlational tests were used to identify which academic and demographic factors were most closely associated with student success in either online or face-to-face course enrollments. The correlation tests were followed by a series of logistic regression analyses. These results were used to create figures and tables for the predict phase of the learning analytics process. The model highlights the likelihood of success for various on-campus students in either online or face-to-face courses.

As part of the predict step, the results were used to identify a specific area with significantly different data. Concurrently enrolled students, those who are simultaneously both high school and college students, were identified as this group.

Act

The act step of this study involved creating recommendations for university personnel on student enrollment strategies, and for instructional designers working with instructors to create both online and face-to-face courses. These recommendations relate back to the data analyzed and current research. Additionally, the recommendations for action include suggestions for further research.

Refine

The refine step of this methodology includes the further analysis of the courses taken as concurrent enrollment courses that were included in this study. Through the refinement process, the reduced dataset was analyzed in an attempt to identify reasons for the variations in final grades for students in courses taken for both high school and college credit.

CHAPTER 4: DATA ANALYSIS AND RESULTS

Introduction

The purpose of this study was to identify what types of students were more successful face-to-face and what types were more successful online. Correlations were used to identify trends for students based on a number of demographic, academic, and course related factors. Then logistic regression tests were completed to identify predictive models for student success. This chapter reports the findings from the quantitative data analysis. The results presented in this chapter are organized into sections on demographics of the study population, the courses addressed in the study, and the enrollment details. The next section reports on the details of the various statistical tests completed as part of this study. The individual research questions will be addressed in Chapter 5 as part of the discussion and conclusions of the study.

Demographics

The study population was determined based on the enrollment choices made by students. It included all students who were actively enrolled in a 100 or 200 level course that was offered in both online and face-to-face formats during all semesters between Fall 2013 and Summer 2015. An actively enrolled student is defined as one who has not dropped the course by the drop date for the term, typically the tenth day of the semester.

Overall

Of the entire student population studied (N = 23,836), 87.6% students (N = 20,875) opted to take a face-to-face course during the study time frame, while only

46.5% of the students (N = 11,076) chose to take a course online. These numbers make it clear that many students are enrolled in a combination of face-to-face and online courses. Of the students, 53.5% (N = 12,760) opted to enroll exclusively in the more traditional face-to-face courses that were included in this study, although there is a possibility they were enrolled in online courses that were excluded from the study. Additionally, 12.4% of the students (N = 2,961) were enrolled in only online courses. The number of students who chose to enroll in a mix of face-to-face and online courses was 34.0% (N = 8,115).

Gender

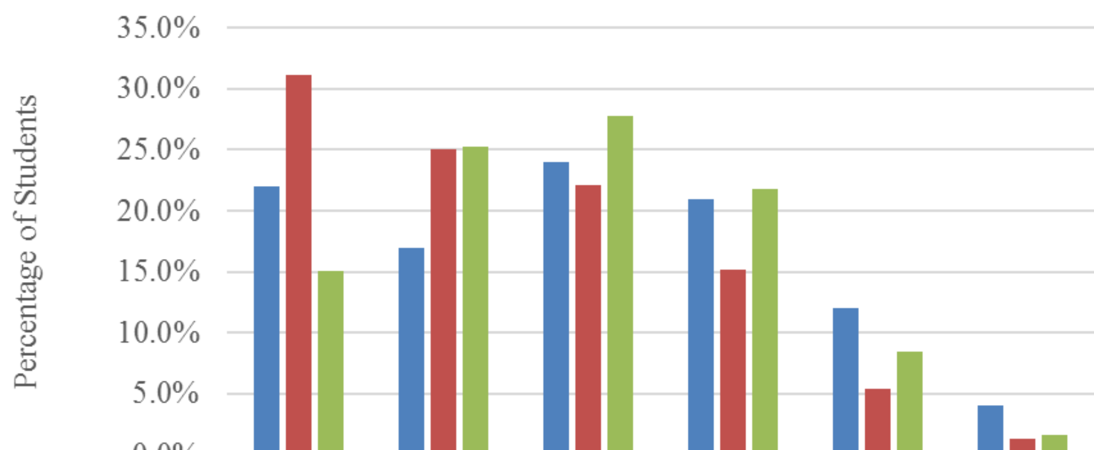
The distribution of students at the university as a whole by gender is split such that 54% of students were female and 45% were male, with approximately 1% opting not to disclose their gender (Office of Communications and Marketing, 2014). Students who opted not to report their gender were omitted from this study. The students in the study population used for this study had a slightly lower percentage of females (52.8%) and a higher percentage of males (47.2%), as compared to the university as a whole. As displayed in Table 3, the gender in the face-to-face courses has a shift from the entire population, with fewer females (51.7%) as compared to males (48.3%). A much higher percentage of females (58.2%) opted to enroll in online courses as compared to the number of males (41.8%).

Table 3 Gender of Students by Course Modality

	Study Population		Face-to-face		Online	
Gender	N	Percent	N	Percent	N	Percent
Female	12,583	52.8%	10,783	51.7%	6,442	58.2%
Male	11,253	47.2%	10,092	48.3%	4,634	41.8%
Total	23,836	100.0%	20,875	100.0%	11,076	100.0%

<u>Age</u>

The age of the students in the study population were categorized into six groups. The percentage of students in each group is shown in Figure 2. The distribution of students into groups by age helped identify traditional aged students (18-24 years old) as compared to nontraditional students. The figure shows data for the entire student population at the university as well as for students within the study population enrolled face-to-face and online. Despite both a higher minimum (13 years old) and maximum (82 years old), face-to-face students (*M* = 22.28, *SD* == 7.17) were slightly younger than the online students (*M* = 24.43, *SD* 7.69) who ranged between 12 and 76 years of age.



	<18	19-20	21-24	25-34	35-49	50+
University	22.0%	17.0%	24.0%	21.0%	12.0%	4.0%
Face-to-face	31.1%	25.0%	22.1%	15.2%	5.4%	1.3%
Online	15.1%	25.3%	27.8%	21.8%	8.4%	1.6%

Figure 2 Distribution of Students by Age

<u>Ethnicity</u>

This ethnic distribution of the study population was very similar to the population of the university as a whole. There was not a significant difference in the proportion of different ethnic groups between the online and face-to-face student groups. Table 4 provides a breakdown of the ethnic groups for the study population as a whole, those enrolled in the face-to-face courses that were part of this study, and those enrolled in the online courses.

Table 4 Ethnicity of Students by Course Modality

	Study Population		Face-to-face		Online	
Ethnicity	N	%	N	%	N	%
American Indian/Alaskan Native	147	0.6%	130	0.6%	68	0.6%
Asian	591	2.5%	528	2.5%	286	2.6%
Black/African American	376	1.6%	339	1.6%	199	1.8%
Caucasian/White	18,064	75.8%	15,626	74.9%	8,516	76.9%
Hispanic/Latino	2,487	10.4%	2,246	10.8%	1,046	9.4%
Native Hawaiian/Pacific Islander	90	0.4%	81	0.4%	45	0.4%
Two or more races	924	3.9%	859	4.1%	409	3.7%
Not Reported	1,157	4.9%	1,066	5.1%	507	4.6%

First Generation Students

In fall of 2014, the university began to collect data as to whether or not students were a first generation college student. Since the data for this study spans the semesters between Fall 2013 and Summer 2015, this data exists for some, but not all students (N = 12,577). Of these students, 44.9% (N = 5,652) are first generation university level students. The majority of the first generation college students, 54.7% (N = 3,089), chose to attend exclusively face-to-face courses, while 9.5% (N = 535) selected only online courses, and 35.9% (N = 2,028) opted for a combination of course delivery modes. Table 5 displays the distribution of the set of known first generation students by gender,

Table 5 First Generation Student Demographics

	N	% of First Generation Population
Gender		
Female	3,159	55.9%
Male	2,493	44.1%
Ethnicity		
American Indian/Alaskan Native	37	0.7%
Asian	119	2.1%
Black/African American	110	2.0%
Caucasian/White	4,043	71.5%
Hispanic/Latino	913	16.1%
Native Hawaiian/Pacific Islander	22	0.4%
Two or more races	277	4.9%
Not Reported	131	2.3%
Age		
≤ 18	1,716	30.4%
19-20	1,314	23.2%
21-24	1,019	18.0%
25-34	1,029	18.2%
35-49	450	8.0%
50+	124	2.2%

ethnicity, and age. There is a slightly higher percentage of females that are first generation students as compared to the population used in this study or for the university as a whole. Additionally, the ethnic distribution of first generation students shifts somewhat from the student population as a whole. There is a higher percentage of Hispanics in the group of first generation students. To account for this shift, there is a lower percentage of whites in the first generation group, as well as fewer Asians. A comparison of the spread of the ages of the first generation students was completed. While there were some minor differences between the study population and this subgroup, there were no noteworthy differences.

Residency

Data on residency was available for approximately 59% of the students included in the study population (N = 14,073). A student identified as a resident established residency in the state in which the university is located, and as a result was charged the in-state tuition rate. Students identified as nonresidents were required to pay the higher out-of-state tuition rates. Table 6 displays the residency status of students based on their residency status. The distribution of students opting for face-to-face as opposed to online courses or a combination of both face-to-face and online courses varies significantly based on residency status. Students that are not residents of the state are much more likely to take a mix of face-to-face and online courses.

Table 6 Residency Status of Students by Course Modality

	Resident		Non-Resident	
	N	Percent	N	Percent
Face-to-face	7,130	63.7%	1,462	50.7%
Online	1,084	9.7%	140	4.9%
Both	2,977	26.6%	1,280	44.4%

Majors/Minors/Certificates

The students that were part of this study (N = 23,836) declared a large number of degrees in the student information system (N = 35,443). When a student is ready to graduate, they need to demonstrate they have met all the requirements for that particular degree. The university allows students to declare majors, minors, and certificates. Alternatively, students have the opportunity to complete classes without declaring a

Table 7 Distribution of Degree Types Declared by Students in Study Population

	N	Percent
Majors	25,029	70.62%
High School - Undeclared	4,243	11.97%
Other		
Minors	5,078	14.33%
Certificates	450	1.27%
Undeclared/Courses of Interest	643	1.81%
Total	35,443	100.00%

degree. Table 7 displays the distribution of the different types of degrees identified in the student information system. Students who have not yet identified a major were distinguished from students taking courses of interest based on the understanding that at some point they would identify a major and complete a degree. Minors and certificates must be completed in conjunction with a major, although that major may be undeclared. Students who took university level courses while still enrolled in high school were identified as such in this field.

Table 8 Number of Degrees Declared by Student in Study Population

	N	Percent
1	15,945	66.89%
2	5,306	22.26%
3	1,789	7.51%
4	556	2.33%
5	169	0.71%
6	53	0.22%
7	14	0.06%
8	2	0.01%
9	2	0.01%

Table 8 displays the number of degrees declared by the students in the study population. While most students declared a single major (66.89%), there were several students who identified multiple degrees with the intention to complete the requirements for each degree. The data did not allow the researcher to identify if students were changing their choice in degree or were declaring an additional degree.

The most recently declared major was labeled as the primary major for each student in the study population. Table 9 displays the distribution of primary major for the students in the study population. The College of Arts and Sciences (COAS) was divided to identify students declaring arts related majors as opposed to those in science and mathematics (STEM) fields. There were an additional 737 students (3.09%) who had taken a college level courses while in high school, but later declared a different major.

Table 9 College or School of Primary Major Declared by Students

	N	Percent
College of Innovation and Design (CID)	7	0.03%
College of Arts and Sciences (COAS) – Arts	4,960	19.68%
College of Arts and Sciences (COAS) – Science	2,376	9.97%
College of Business and Economics (COBE)	4,531	19.01%
College of Education (COED)	903	3.79%
College of Engineering (COEN)	2,424	10.17%
College of Health Sciences (COHS)	5,015	21.04%
School of Public Service (SPS)	1,804	7.57%
Undeclared – Courses of Interest	403	1.69%%
Undeclared – High School	1,683	7.06%
Total	23,836	100.00%

Courses

The students included in this study (N = 23,836) were enrolled in courses that were offered in both online and face-to-face modalities during the time period between Fall 2013 and Summer 2015. Enrollments from 2,811 unique course sections were included in the study. Table 10 shows the distribution of course sections across modalities and semesters offered. During the fall and spring semester, face-to-face course sections outnumber the online course sections. During the fall semester, face-to-face courses were 80% of the course offerings, that number fell in the spring semester to approximately 72%. The summer semester had a different proportion of face-to-face and online course sections. In the summer terms included in this study, online sections made up 57% of the course sections.

Table 10 Course Sections by Modality and Term

	Semester Offered							
	FA13	SP14	SU14	FA14	SP15	SU15	Total	Percent
Face-to-face	549	406	69	540	381	86	2,031	72%
Online	134	148	91	144	152	111	780	28%
Total	683	554	160	684	533	197	2,811	100%

The set of courses included in this study were offered by 29 of the 61 different academic departments across the university. Many of the courses included in the study are selected by students to meet the core graduation requirements, while others are chosen by a more select audience as part of a specific program, to fulfill the requirements of a major, minor, or certificate. The number of courses offered by each department in each modality can be reviewed in Table 11.

Table 11 Courses Offered by Academic Department

Academic Department	Sections Online	Face-to-face	Total
Academic Advising and Enhancement	9	19	28
College of Arts and Sciences	547	1,494	2,041
Anthropology	32	25	57
Art	22	20	42
Biology	64	87	151
Chemistry	15	40	55
Communications	1	1	2
English	152	424	576
Environmental Studies	9	22	31
Geography	6	4	10
History	49	83	132
Humanities	19	12	31
Mathematics	61	520	581
Philosophy	22	72	94
Psychology	10	45	55
Sociology	49	55	104
Theater Arts	26	41	67
World Languages	10	43	53
College of Business and Economics	51	129	180
Accountancy	4	13	17
Economics	19	53	72
Management	11	20	31
Marketing and Finance	17	43	60
College of Education	25	22	47
Educational Technology	17	16	33
Special Education	8	6	14
College of Engineering	13	11	24
College of Health Studies	82	102	184
Community and Environmental Health	75	54	129
Kinesiology	7	48	55
Foundational Studies	28	162	190

Academic Department	Sections		
	Online	Face-to-face	Online
School of Public Service	25	92	117
Criminal Justice	17	49	66
Political Science	8	43	51
Grand Total	780	2,031	2,811

Enrollments

The students in the study population represent 100,943 different course enrollments throughout the two year, six semester time frame. Of the enrollments, 78.47% were in face-to-face courses (N = 79,213) as compared to 21.44% that were completely online (N = 21, 730). The students enrolled in courses ranged from freshman status to graduate students. The academic level is determined by the number of credits earned by a student prior to the beginning of the term. The distribution of academic level of students enrolled in the classes included in the study can be seen in Figure 3.

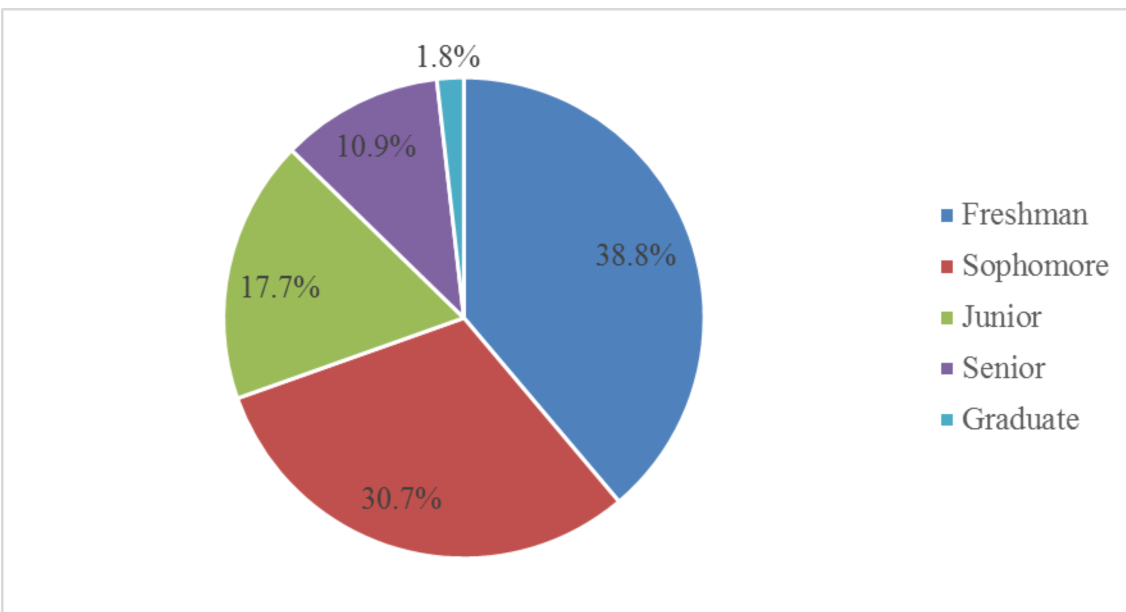
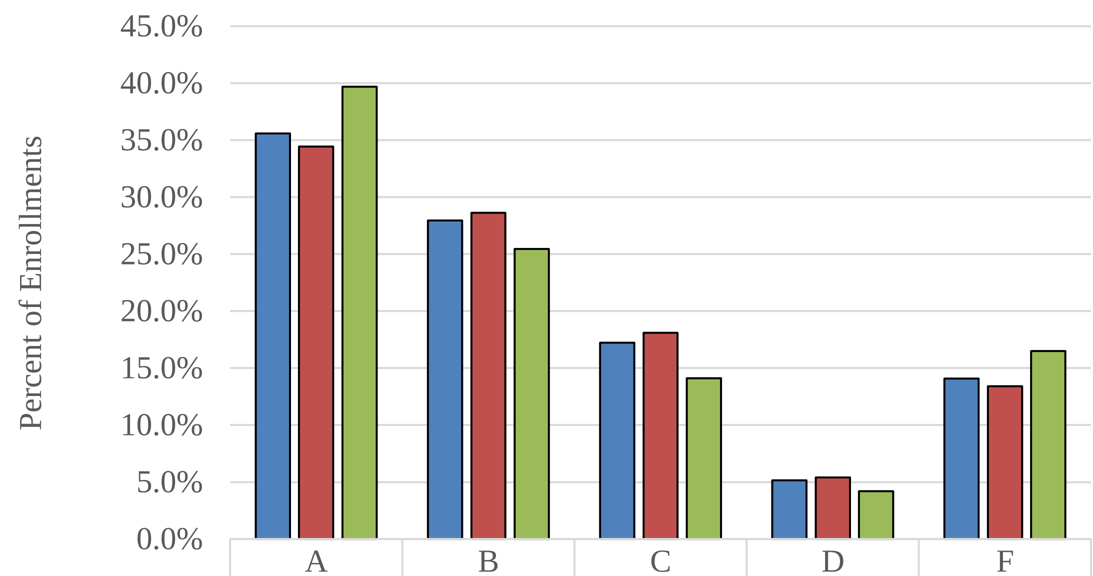


Figure 3 Academic Level of Students at Time of Enrollment

The academic load of the students that carried these enrollments included in this study varied. The vast majority (83.5%) of the enrollments were for students enrolled full-time at the university. The remaining enrollments were students enrolled on a part-time basis (16.5%).

<u>Grades Earned</u>

Grades earned as a result of the courses completed for the entire study population and for both course modalities are displayed in Figure 4. The mean grade point average (GPA) for all course enrollments in the study population was M = 2.658 (SD = 1.372). The GPA for only face-to-face enrollments (M = 2.653, SD = 1.352) was slightly lower, while the online GPA (M = 2.676, SD = 1.445) was somewhat higher than that of the population. In contrast, when reclassifying final grades as successful, a letter grade of C



	A	B	C	D	F
Sample	35.6%	28.0%	17.2%	5.1%	14.1%
Face-to-Face	34.5%	28.6%	18.1%	5.4%	13.4%
Online	39.7%	25.5%	14.1%	4.2%	16.5%

Figure 4 Final Grades Earned in Courses Included in Study Population

or higher, or unsuccessful, a D or lower, the results were different. There was a significant difference in enrollment success based on course modality. The mean success rate for face-to-face students (*M* = 0.812, *SD* = 0.391) was higher than the success rate for online enrollments (*M* = 0.793 *SD* = 0.405).

A full comparison of GPAs by various demographic and academic characteristics is shown in Table 12. A review of the table can be completed to identify which values for the characteristics had higher final grade averages than their counterparts for each variable in the population as a whole as well as for both the face-to-face and online subsets.

Course Subjects

So far, the comparison of final grades and success have been focused on student based factors, either demographic or academic. Another area that was found to be a differentiating factor in the final grade and success in a course was the subject of the

course the student was enrolled in. The descriptive statistics for each of the individual courses are listed in Table 13. Comparisons revealed a number of courses in which students earned significantly higher grades than other courses. For the entire study population, students enrolled in courses offered by the following departments had significantly higher grades than the other departments: Academic Advising and Enhancement, Kinesiology, Communications, Special Education, and Educational Technology. This same list of classes differs when restricting to only face-to-face course enrollments: Communications and Academic Advising and Enhancement. For online.

Table 12 Descriptive Statistics for Grade Value of Enrollments

	Study Population			Face-to-Face			Online		
	Mean	St Dev	N	Mean	St Dev	N	Mean	St Dev	N
Enrollments	2.658	1.373	100,943	2.653	1.352	79,213	2.676	1.445	21,730
Demographic Variables									
Gender									
Female	2.752	1.348	53,965	2.771	1.315	40,557	2.694	1.440	13,408
Male	2.551	1.393	13,978	2.530	1.378	38,656	2.646	1.453	8,322
Ethnicity									
American Indian/Alaska Native	2.408	1.484	611	2.362	1.462	472	2.561	1.552	139
Asian	2.897	1.323	2,528	2.874	1.326	2,017	2.990	1.307	511
Black/African American	2.386	1.390	1,853	2.392	1.362	1,427	2.364	1.483	426
Caucasian	2.682	1.371	74,946	2.681	1.350	58,167	2.685	1.444	16,779
Hispanic/Latino	2.570	1.358	10,965	2.566	1.343	8,978	2.585	1.426	1,987
Hawaiian/Pacific Islander	2.434	1.408	389	2.335	1.406	284	2.704	1.386	105
Two or More Races	2.555	1.401	4,530	2.547	1.383	3,643	2.589	1.470	887
Not Reported	2.625	1.362	5,121	2.593	1.334	4,225	2.779	1.479	896
Age Category									
$\leq$ 18	3.863	1.353	25,862	2.871	1.254	23,849	2.767	1.389	2,013
19-20	2.636	1.353	33,580	2.623	1.338	27,561	2.695	1.415	6,019
21-24	2.463	1.429	21,426	2.411	1.410	14,974	2.583	4.464	6,452
25-34	2.585	1.447	13,346	2.539	1.429	9,391	2.673	1.476	4,955
35-49	2.738	1.431	4,713	2.718	1.416	2,796	2.767	1.452	1,917
50 +	2.969	1.339	1,016	2.914	1.363	642	3.064	1.294	374

	Study Population			Face-to-Face			Online		
	Mean	St Dev	N	Mean	St Dev	N	Mean	St Dev	N
First Generation									
Reported First Generation	2.542	1.410	27,669	2.554	1.386	22,455	2.494	1.507	5,214
Reported Non-First Generation	2.745	1.352	35,636	2.742	1.335	29,929	2.758	1.442	5,707
Residency Status									
Resident	2.626	1.402	44,587	2.631	1.383	36,841	2.603	1.491	7,672
Non-Resident	2.883	1.235	18,587	2.888	1.212	15,965	2.850	1.369	2,622
Academic Variables									
Academic Level									
Freshman	2.619	1.391	39,183	2.647	1.369	35,452	2.356	1.554	3,731
Sophomore	2.636	1.366	31,030	2.644	1.338	24,329	2.605	1.465	6,701
Junior	2.654	1.362	17,881	2.619	1.342	12,012	2.727	1.400	5,869
Senior	2.783	1.336	11,018	2.697	1.328	6,337	2.900	1.337	4,681
Graduate	3.171	1.258	1,831	3.209	1.220	1,083	3.118	1.311	748
Academic Load									
Full-time	2.627	1.373	84,307	2.619	1.357	68,273	2.662	1.442	16,034
Part-time	2.816	1.358	16,636	2.867	1.305	10,940	2.717	1.453	5,696
Term of Enrollment									
Fall	2.660	1.368	52,691	2.667	1.354	44,111	2.623	1.442	8,580
Spring	2.631	1.380	41,401	2.619	1.356	32,460	2.674	1.461	8,941
Summer	2.809	1.353	6,851	2.840	1.256	2,642	2.790	1.410	4,209

	Study Population			Face-to-Face			Online		
	Mean	St Dev	N	Mean	St Dev	N	Mean	St Dev	N
Primary Major College									
CID	2.818	1.352	44	2.906	1.304	32	2.583	1.505	12
COAS – Arts	2.598	1.384	21,566	2.618	1.355	16,519	2.532	1.472	5,047
COAS – Sciences	2.619	1.409	9,620	2.611	1.398	7,872	2.653	1.456	1,748
COBE	2.673	1.359	19,400	2.673	1.340	15,745	2.677	1.437	3,655
COED	2.731	1.371	3,285	2.729	1.336	2,382	2.735	1.460	903
COEN	2.561	1.417	10,726	2.511	1.412	8,653	2.767	1.419	2,073
COHS	2.716	1.355	25,269	2.693	1.336	2,382	2.783	1.422	6,318
SPS	2.611	1.332	6,647	2.619	1.304	5,235	2.583	1.730	1,412
Undeclared – Courses of Interest	2.157	1.526	1,699	2.054	1.508	1,306	2.499	1.537	393
Undeclared – High School Credit	3.363	0.862	2,687	3.387	0.828	2,518	3.006	1.213	169

Table 13 Descriptive Statistics for Grade Value by Course Subject

	Study Population				Face-to-Face				Online			
	Rank	Mean	Std Dev	N	Rank	Mean	Std Dev	N	Rank	Mean	Std Dev	N
Academic Advising and Enhancement	1	3.496	1.012	450	2	3.588	0.911	325	2	3.256	1.211	125
Accounting	11	2.965	1.428	482	9	3.091	1.365	372	19	2.536	1.554	110
Anthropology	23	2.573	1.335	2,767	22	2.636	1.277	1,878	22	2.439	1.441	889
Art	14	2.826	1.268	3,215	20	2.717	1.294	2,260	5	3.085	1.167	955
Biology	29	2.383	1.287	7,724	28	2.346	1.279	6,148	20	2.527	1.309	1,576
Business Communications	13	2.946	1.186	1,600	12	2.923	1.143	1,137	7	3.000	1.286	463
Chemistry	31	2.275	1.391	4,505	33	2.248	1.378	4,172	16	2.613	1.506	333
Chinese	22	2.607	1.466	178	16	2.796	1.324	137	30	1.976	1.739	41
Communications	3	3.294	1.359	17	1	3.846	0.554	13	33	1.500	1.732	4
Criminal Justice	28	2.424	1.269	2,565	27	2.432	1.267	2,151	24	2.382	1.279	414
Economics	21	2.617	1.336	4,460	21	2.707	1.304	3,933	31	1.945	1.383	527
Educational Technology	5	3.168	1.486	708	4	3.318	1.455	358	6	3.014	1.504	350
Engineering	7	3.063	1.374	1,366	32	2.256	1.295	355	1	3.346	1.286	1,011
English	9	3.030	1.320	11,699	7	3.110	1.278	9,034	12	2.761	1.421	2,665
Environmental Health	6	3.079	1.131	391	8	3.104	1.099	376	21	2.467	1.685	15
Environmental Studies	15	2.802	1.195	822	15	2.820	1.162	656	13	2.729	1.318	166

	Study Population				Face-to-Face				Online			
	Rank	Mean	Std Dev	N	Rank	Mean	Std Dev	N	Rank	Mean	Std Dev	N
French	20	2.669	1.451	242	19	2.744	1.369	215	28	2.074	1.920	27
General Business	17	2.776	1.106	1,317	14	2.826	1.122	1,043	17	2.584	1.025	274
Geography	25	2.523	1.489	172	25	2.506	1.533	83	18	2.539	1.454	89
Health Studies	8	3.046	1.271	5,386	6	3.188	1.077	1,658	8	2.983	1.344	3,728
History	24	2.539	1.404	3,781	24	2.621	1.341	2,767	25	2.315	1.540	1,014
Humanities	18	2.727	1.421	714	13	2.856	1.293	285	15	2.641	1.495	429
Japanese	33	2.223	1.574	251	31	2.278	1.544	198	29	2.019	1.681	53
Kinesiology	2	3.343	0.982	1,223	3	3.364	0.961	1,085	4	3.174	1.120	138
Korean	26	2.500	1.743	52	23	2.625	1.705	40	27	2.083	1.881	12
Mathematics	32	2.265	1.423	18,168	29	2.313	1.404	16,048	32	1.899	1.507	2,120
Philosophy	27	2.429	1.420	2,777	26	2.502	1.393	2,187	26	2.159	1.487	590
Political Science	19	2.715	1.267	1,840	18	2.754	1.224	1,645	23	2.390	1.547	195
Psychology	30	2.336	1.393	5,251	30	2.310	1.392	4,890	14	2.681	1.363	361
Sociology	16	2.790	1.322	4,242	17	2.757	1.262	2,723	11	2.848	1.421	1,519
Special Education	4	3.241	1.087	502	5	3.243	1.049	272	3	3.239	1.133	230
Theater Arts	10	3.027	1.257	2,530	10	3.065	1.228	1,881	9	2.917	1.332	649
University Foundations	12	2.957	1.298	9,546	11	2.965	1.284	8,888	10	2.853	1.471	658

courses, the list includes the following course subjects: Engineering, Academic Advising and Enhancement, Special Education, and Kinesiology.

Correlation Comparisons

A correlation comparison was completed using most of the numerical variables in the dataset. The comparison was completed using the entire data set (N = 100,943). There are many variables that have little to no correlation. However, there are some areas where relationships are worthy of note. Every variable had similar levels of correlation when looking at the same variables for face-to-face enrollments as compared to online course enrollments

When looking at the entire population, there is a strong positive relationship between the grade earned in a course and the GPA earned for the term the course was taken ($r = 0.699$, $p < 0.0001$), while the correlation between grade earned and a student's cumulative GPA is a moderately positive relationship ($r = 0.5438$, $p < 0.0001$). Similar correlations exist when looking at only the face-to-face enrollments (N = 79,213). There is a strong positive relationship between grade earned in a course and the GPA earned for the term the face-to-face course was completed ($r = 0.6686$, $p < 0.0001$). The correlation between grade earned and a student's cumulative GPA is a moderately positive relationship ($r = 0.5407$, $p < 0.0001$). Like the face-to-face students, online enrollments (N = 21,730) have correlations between GPA and final grade. There is a very strong positive relationship between grade earned in a course and the GPA earned for the term the online course was completed ($r = 0.8084$, $p < 0.0001$). The correlation between grade earned and a student's cumulative GPA is a moderately positive relationship ($r = 0.5753$, $p < 0.0001$). Similar correlations exist when comparing success in a course, passing the course with a C or better, and both term and cumulative GPAs. These relationships are for the study population as a whole in addition to both the face-to-face and online enrollments.

Another area in which positive correlations exist is between the age of a student at the time of enrollment and their academic level. The study population ($r = 0.4673$, $p < 0.0001$) and both the face-to-face ($r = 0.4672$, $p < 0.0001$) and online ($r = 0.4676$, $p < 0.0001$) groups have moderate positive relationships between the academic level and the age of the students. This meaning the older a student is at the time of enrollment they are more likely to be an upperclassman.

There are weak positive relationships between the various ACT test scores and GPA, both for the term of enrollment and for the cumulative GPA. There are varying levels of positive correlations between the various ACT exams scores, with the strongest correlations being the relationship between the component tests and the composite score. There are weak negative relationships between the various ACT test, math, verbal, written, and composite scores and a student's age.

Logistic Regression Results

To address the first three research questions, logistic regression tests were conducted to investigate the extent to which various demographic, academic, and course related factors can be used to predict success. These analyses were completed for the entire study population as well as for the face-to-face and online subsets. For each group, the entire study population, the face-to-face enrollments, and the online enrollments, there were a series of four different logistic regression models created in the process of identifying the best model for predicting success. Separate logistic regression models were created for demographic variables, academic variables, and course variables to identify if one area had a larger influence than the others prior to creating a full model using all the variables. As part of the process of identifying the best prediction model, different selection models were used including forward selection, backward elimination, and stepwise selection as well as the full fitted model with no selection. The full fitted model provided the greatest accuracy of prediction for all data sets.

Demographic Variables

The first model was limited to demographic variables. For this model, the Nagelkerke R^2 estimate reflects the variability of success that can be attributed to the variables included in the logistic regression model. The combination of demographic variables used in the model accounts for a 2.91% influence on the likelihood of success (R^2 = 0.0291). Because the model explains such a low percentage of the likelihood of success, the model was only an accurate predictor 59.17% of the time, based on the area under the curve (ROC Curve Model). Demographic variables accounted for a slightly higher amount of the likelihood of success for the face-to-face enrollments, 3.19%. Based on the ROC Curve Model, demographic variables were accurate in predicting face-to-face success 59.83% of the time. The demographic variables accounted for 2.26% of the likelihood of success for online enrollments based on the Nagelkerke R^2 estimate, a lower percentage than the face-to-face subset. As a result, demographic variables were accurate in predicting success only 57.99% of the time for online enrollments based on the ROC Curve Model. A summary of the logistic regression model for demographic variables can be reviewed in Table 14.

Table 14 Logistic Regression Summary for Subset Models

Model Variables	Demographic	Academic	Course
Full Study Population			
X^2	1,051.1858	22,324.5119	2,416.9195
N	57,397	100,943	100,943
Significance	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
Degrees of Freedom	11	21	14
Nagelkerke's Pseudo R^2	0.0291	0.3179	0.0379
Area Under ROC Curve	0.5917	0.8266	0.6110
Face-to-Face			
X^2	954.7563	18,187.6186	2,318.5826
N	48,117	79,213	79,213
Significance	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
Degrees of Freedom	11	21	14
Nagelkerke's Pseudo R^2	0.0319	0.3310	0.0482
Area Under ROC Curve	0.5983	0.8306	0.6242
Online			
X^2	138.1273	5,287.4567	543.4994
N	9,280	21,730	21,730
Significance	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
Degrees of Freedom	11	21	14
Nagelkerke's Pseudo R^2	0.0226	0.3377	0.0386
Area Under ROC Curve	0.05799	0.82.53	0.6127

Academic Variables

A separate model was created to evaluate the effect of academic variables on success in courses. The Nagelkerke R^2 estimate showed that academic variables accounted for 31.97% of the likelihood of success across the study population, and the area under the curve indicated the model was accurate in predicting success 82.66% of the time. For the face-to-face enrollments, the academic variables explained 33.10% of the variability in the likelihood of success, based on the Nagelkerke's R^2 estimate, and the ROC Curve Model indicated academic variables were an accurate as a predictor for 83.06% of the face-to-face dataset. For online enrollments, academic variables represent 33.77% of the variability in the likelihood of success. This model is accurate in predicting student success 82.53% of the time, based on the ROC Curve Model. By far the most significant variable in this model was the cumulative GPA. The term GPA was omitted from this and all other logistic regression models because of the collinearity with the target variable.

Course Variables

This model evaluated variables specifically related to the course a student took. The Nagelkerke's R^2 estimate indicated that *c*ourse related variables influenced 3.79% of the likelihood of success. When the course variables were used as a prediction model for the study population the area under the curve showed the model was accurate 61.10% of the time. The course related variables were also statistically significant for face-to-face course enrollments. The face-to-face accounted for a slightly higher percentage of the effect on student success 4.82% based on Nagelkerke's estimate. The ROC Curve Model identified this model was accurate in predicting success 62.03% of the time. For online enrollments, course related variables accounted for 3.86% of the variability in the success for online course enrollments according to Nagelkerke's R^2 estimate. When used to predict success, the area under the curve was accurate in identifying successful online students 61.27% of the time.

Full Prediction Model

While each of the models described above addresses some aspects of the predictors of success for students, the full model includes all variables that showed significance through the correlation analysis. Table 14 shows the relative level of predictability for each set of variables, but the full model was found to be the most significant predictor.

The test of the full model, was statistically significant for the study population, $X^2(46, N = 57{,}397) = 18{,}202.7063$, $p < 0.0001$. The Nagelkerke R^2 estimate indicated the combination of variables used in the final model account for a 42.13% influence on the likelihood of success. According to the ROC Curve Model, this model correctly predicted success for 86.74% of the students in the study population, with a sensitivity of 94.5% and a specificity of 45.3%.

To illustrate the predictive nature of the logistic regression, the logistic model can be written in the form of a mathematical equation. This equation is most often presented as a logit equation that is in the form of Equation 1 where Y is the dependent variable of the logistic regression, P is the probability of the desired outcome, and α and β are the coefficients of the regression model (Peng, Lee, & Ingersoll, 2002). Equation 1 can be manipulated to represent the probability of the desired outcome, or in the case of this study, the probability of success. The probability equation is shown in Equation 2.

$$\text{Logit}(Y) = \ln(odds) = \ln\left(\frac{P}{1-P}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (1)$$

$$P(Y) = \frac{e^{\alpha+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n}}{1+e^{\alpha+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n}} \quad (2)$$

Equation 3 shows the full model for the study population. The equation contains categorical variables and continuous variables. For the continuous variables in the equation, if the variable is true, then the coefficient is included in the equation, but if the variable value is false, the variable is equal to zero, and as a result, the coefficient is eliminated from the equation. For continuous variables, the numeric value is substituted in for the variable. Variables that were not significant ($p < 0.05$) were not included in the logit equation.

Logit(Success $_{\text{Study Population}}$) = – 0.0478 (Full-time Status) + 0.8039 (AAE Course) – 0.2046 (COAS-Arts Course – 0.7745 (COAS-Science Course) – 0.2259 (COBE Course) + 0.3568 (COEN Course) + 0.2631 (COHS Course) + 0.1618 (FS Course) – 2.559 (Cumulative Credits Earned) + 1.9069 (Cumulative GPA) + 0.4619 (Degree Count) – 1.1156 (Bachelor Degree Type) + 2.9707 (HS Credit Degree Type) + 0.1371 (Hispanic Ethnicity) + 0.1030 (Not First Generation) – 0.2576 (Course Section Not Full) – 0.1899 (2 Credit Course) + 0.1296 (3 Credit Course) + 0.0948 (Nonresident Status) – 0.0676 (Term Credits Attempted) + 0.3096 (Fall Enrollment) + 0.0544 (Spring Enrollment) – 0.3692 (Total Course Enrollment) (3)

For the face-to-face enrollments, the logistic regression was statistically significant for the full model, $X^2(46, N = 48{,}117) = 15{,}194.5884$, $p < 0.0001$. The variables included in the model explained 43.92% of the variability in the likelihood of success and was accurate as a predictor for 87.43% of the face-to-face data subset. The equation that represents the face-to-face logit model is displayed in Equation 4.

Logit(Success $_{\text{Face-to-Face}}$) = – 0.6267 – 0.0450 (Full-time Status) + 0.0517 (100 Level Course) + 1.4781 (AAE Course) – 0.2835 (COAS-Arts Course) – 0.8864 (COAS-Science Course) – 1.0227 (COEN Course) + 1.1024 (COHS Course) – 2.6963 (Cumulative Credits Earned) + 1.9502 (Cumulative GPA) + 0.45592 (Degree Count) – 0.8936 (Bachelor Degree Type) + 2.6152 (HS Credit Degree Type) + 0.1164 (Hispanic Ethnicity) – 0.0450 (No Race Reported) + 0.0900 (Not First Generation) – 0.2737 (Course Section Not Full) – 0.1915 (COAS-Science Major) – 0.4258 (1 Credit Course) + 0.2242 (3 Credit Course) + 0.1135 (Nonresident Status) – 0.0920 (Term Credits Attempted) + 0.2654 (Fall Enrollment) – 0.5011 (Total Course Enrollment) (4)

The model was statistically significant for online enrollments, $X^2(46, N = 9{,}280) = 3071.1300$, $p < 0.0001$. The Nagelkerke R^2 estimate indicated that the variables included in the model represent 43.16% of the variability in the likelihood of success. This model is accurate in predicting student success 85.95% of the time based on the ROC Curve Model. Equation 5 shows the relationship between the significant variables and the coefficients for the model to predict online success.

Logit(Success $_{\text{Online}}$) = – 2.3066 – 0.8496 (COAS-Science Course) – 0.5257 (COBE Course) + 1.0473 (COEN Course) + 2.1530 (Cumulative GPA) – 0.6119

(Degree Count) – 1.9378 (Bachelor Degree Type) + 4.2345 (HS Credit Degree Type) + 0.0917 (Not First Generation) – 0.1997 (Course Section Not Full) – 0.0721 (Female) + 0.3317 (COBE Major) – 0.4970 (2 Credit Course) – 0.1058 (Spring Enrollment) (5)

Another way to look at the significance of the variables is with the odds ratio. The odds ratio is calculated as the ratio of success for the given value of a variable as compared to the base value. For example, more students in the study population were sophomores than any other academic level, so sophomores were considered the base value and all other academic levels were compared to them in determining their relative likelihood of success. As can be seen in Table 15, a freshman is 0.934 times as likely to be successful in a course as compared to a sophomore when not discriminating between face-to-face and online enrollments. That means that a freshman is somewhat less likely to successfully complete their course as compared to a sophomore. Similarly, a student enrolled in an AAE course is 2.508 times more likely to successfully complete their course as compared to a student in an SPS course. For numeric variables, each unit of increase in the odds ratio is associated with one unit of increase in the given variable. For example, looking at the cumulative GPA, a student is 6.732 times more likely to be successful for each additional full point increase in their cumulative GPA. While this information is valuable, only some of the variables were identified as significant when calculating the logistic regression for the model.

Table 15 Full Logistic Regression Models for Success

Variable	Study Population		Face-to-face		Online	
	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio
X^2	17,477.9518		15,194.5884		3,0071.1300	
N	57,397		48,117		9,280	
Significance	$p < 0.0001$		$p < 0.0001$		$p < 0.0001$	
Degrees of Freedom	46		46		46	
Cox and Snell R^2	0.2625		0.2708		0.2818	
Nagelkerke's Pseudo R^2	0.4213		0.4392		0.4316	
Area Under ROC Curve	0.8674		0.8743		0.8595	
Intercept	0.2434		-0.6267 *		-2.3066 **	
Academic Level						
Freshman	-0.0432	0.934	-0.0539	0.896	0.0303	1.146
Junior	0.0187	0.994	0.0178	0.963	0.0306	1.146
Senior	0.0304	1.006	0.0291	0.973	0.0268	1.142
Graduate	-0.0303	0.947	-0.0490	0.900	0.0179	1.131
Base = Sophomore						
Academic Load						
Full-time	-0.0478 *	0.909	0.0450 *	0.914	-0.0641	0.880
Base = Part-time						

Significance Levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

† Variable was transformed for calculation.

Variable	Study Population		Face-to-face		Online	
	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio
Age at Course Start †	-0.1116	0.894	-0.4202	0.657	0.9673	2.631
Course Level						
100	0.0247	1.051	0.0517 *	1.109	0.0396	1.082
Base = 200						
College Offering Course						
AAE	0.8039 *	2.508	1.4781 *	5.585	0.3170	1.480
COAS – Arts	-0.2046 **	0.915	-0.2835 **	0.959	0.0700	1.156
COAS – Science	-0.7745 ***	0.517	-0.8864 ***	0.525	-0.8496 ***	0.461
COBE	-0.2259 **	0.896	-0.1578	1.088	-0.5257 **	0.637
COEN	0.3568 *	1.604	-1.0227 ***	0.458	1.0473 ***	3.072
COED	-0.2649	0.861	-0.1153	1.135	-0.0479	1.027
COHS	0.2631 **	1.461	1.1024 ***	3.836	-0.0159	1.061
FS	0.1618 *	1.320	0.1271	1.446	0.0797	1.167
Base = SPS						
Cumulative Credits Earned †	-2.5590 ***	0.077	-2.6963 ***	0.067	-0.2623	0.769
Cumulative GPA †	1.9069 ***	6.732	1.9502 ***	7.030	2.1530 ***	8.611
Degree Count †	0.4619 ***	1.587	0.5592 ***	1.749	-0.6119 **	0.542

Significance Levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

† Variable was transformed for calculation.

Variable	Study Population		Face-to-face		Online	
	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio
Degree Type						
Bachelor	-1.1156 ***	2.095	-0.8936 **	2.289	-1.9378 **	1.432
HS Credit	2.9707 ***	124.687	2.6152 ***	76.465	4.2345 **	686.281
Base = Other						
Ethnicity						
American Indian/Alaskan	-0.1793	0.783	-0.2059	0.738	0.0564	1.053
Asian	0.1662	1.106	0.1198	1.022	0.3620	1.429
Black	-0.0988	0.848	-0.0178	0.890	-0.1491	0.857
Hispanic	0.1373 **	1.074	0.1164 *	1.018	0.1805	1.192
Pacific Islander	-0.1570	0.800	-0.1769	0.759	-0.0827	0.916
Two or More Races	0.0691	1.003	0.1370	1.039	-0.2217	0.856
No Race Reported	0.0031	0.934	-0.0450 *	0.844	-0.1506	0.797
Base = Caucasian						
First Generation Status						
No	0.1030 ***	1.229	0.0900 ***	1.197	0.0917 **	1.201
Base = Yes						
Full Course Section						
No	-0.2576 ***	0.597	-0.2737 ***	0.578	-0.1997 ***	0.671
Base = Yes						

Significance Levels: * $p < 0.05$, ** p < 0.01, *** $p < 0.0001$
† Variable was transformed for calculation.

Variable	Study Population		Face-to-face		Online	
	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio
Gender						
Female	-0.0225	0.956	0.0128	1.026	-0.0721 *	0.866
Base = Male						
Primary Major College						
CID	-0.2783	0.484	-0.4210	0.429	0.9540	1.134
COAS – Arts	-0.0661	0.599	-0.1101	0.586	0.1524	0.509
COAS – Sciences	-0.1203	0.567	-0.1915 *	0.540	0.2113	0.540
COBE	0.0275	0.657	-0.0182	0.642	0.3317 *	0.609
COEN	-0.0658	0.599	-0.1118	0.585	0.2714	0.573
COED	-0.0824	0.589	-0.1264	0.576	0.1537	0.509
COHS	-0.0515	0.608	-0.0785	0.605	0.2574	0.565
HS Credit	0.1902	0.774	0.6331	1.232	-3.1602	0.019
Base = Undeclared						
Number of Credits						
1.0	-0.0852	0.794	-0.4258 *	0.502	0.4637	1.474
2.0	-0.1899 *	0.715	-0.0609	0.724	-0.4970 **	0.564
3.0	0.1296 *	0.984	0.2242 **	0.963	-0.0421	0.889
Base = 4.0						

Significance Levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$
† Variable was transformed for calculation.

Variable	Study Population		Face-to-face		Online	
	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio	Est. (β)	Odds Ratio
Residency Status						
Nonresident	0.0948 ***	1.209	0.1135 ***	1.255	0.0296	1.061
Base = Resident						
Term Credits Attempted	-0.0676 ***	0.935	-0.0920 ***	0.912	0.0019	1.002
Term of Enrollment						
Fall	0.6096 ***	1.961	0.2654 ***	1.740	-0.0586	0.800
Spring	0.0544 *	1.520	0.0231	1.366	-0.1058 *	0.763
Base = Summer						
Total Enrolled (Class Size) †	-0.3692 ***	0.691	-0.5011 ***	0.606	0.0836	1.087

Significance Levels: * $p < 0.05$, ** p < 0.01, *** $p < 0.0001$

† Variable was transformed for calculation.

Research Question 4 – Further Analysis

During the logistic regression analysis, the courses taken by students that were also enrolled in high school stood out as significantly different than other course enrollments. These enrollments were identified as the area in need of further analysis. The odds ratio for students with high school as their degree type were 124.687 times more likely to be successful as compared to post-secondary students. The odds fell somewhat for the face-to-face enrollments with the odds of successful completion being 76.465 times that of students who were working toward a non-bachelor's degree. In the online enrollments, the odds were the most significant with the odds being 686.281 times that of the students who listed other as their degree type. Table 16 shows the distribution of concurrent enrollments students within several of the key factors.

The mean final grade for all students with high school credit as their declared major in the study population was $M = 3.363$ ($SD = 0.862$). A one-way analysis of variance (ANOVA) test was completed to compare the final grade for concurrently enrolled high school students to students who had completed high school. There was a significant difference in final grade based on high school as a primary major, $F(1, 100{,}941) = 732.54$, $p < 0.0001$. Post hoc comparisons using Tukey's HSD test indicated that the mean final grade for students who have completed high school ($M = 2.639$, $SD = 1.379$) was significantly lower than the final grade (GPA) for concurrently enrolled students in the study population.

The concurrent student GPA for only face-to-face enrollments ($M = 3.387$, $SD = 0.828$) was slightly higher, while the online GPA ($M = 3.006$, $SD = 1.213$) was somewhat lower than that of the study population. An (ANOVA) test was completed on final grade

Table 16 Distribution Statistics for Concurrent Enrollments Students

	Study Population	Face-to-face	Online
Total Enrollments (N)	2,687	2,518	169
Ethnicity			
American Indian	0.33%	0.32%	0.59%
Asian	1.79%	1.83%	1.18%
Black	0.89%	0.91%	0.59%
Caucasian	79.87%	79.47%	85.80%
Hispanic	9.94%	10.13%	7.10%
Pacific Islander	0.22%	0.24%	0.00%
Two or More Races	4.39%	2.62%	2.96%
No Race Reported	2.57%	4.49%	1.78%
Gender			
Female	61.85%	61.56%	66.27%
Male	38.15%	38.44%	33.73%
College Offering Course			
AAE	4.84%	3.73%	21.30%
COAS - Arts	31.93%	29.31%	71.01%
COAS - Sciences	34.87%	36.78%	6.51%
COBE	7.74%	8.26%	0.00%
COED	0.04%	0.04%	0.00%
COEN	0.15%	0.12%	0.59%
COHS	9.86%	10.48%	0.59%
FS	0.41%	0.44%	0.00%
SPS	10.16%	10.84%	0.00%
Final Grade			
A	55.2%	55.6%	47.9%
B	31.0%	31.5%	23.7%
C	10.5%	10.1%	16.0%
D	1.7%	1.4%	5.9%
F	1.7%	1.4%	6.5%
Average	3.363	3.387	3.006
Standard Deviation	0.862	0.862	0.859
Success Rate	96.65%	97.26%	87.57%

within the course modality subsets. There was a significant difference in final grade based on high school enrollment status for face-to-face course enrollments, $F(1, 79{,}213) = 772.71$, $p < 0.0001$. Post hoc comparisons using Tukey's HSD test indicated that the mean final grade for students who have completed high school ($M = 2.639$, $SD = 1.359$) was significantly lower than the mean final grade for concurrently enrolled students in the face-to-face enrollments. Additionally, there was a significant difference in final grade based on high school enrollment status for online course enrollments, $F(1, 21{,}730) = 8.86$, $p = 0.0029$. Post hoc comparisons using Tukey's HSD test indicated that the mean final grade for students who have completed high school ($M = 2.674$, $SD = 1.446$) was significantly lower than the GPA for concurrently enrolled students in the online subset.

Summary of Analysis

The analysis of data for this study was completed to build evidence to answer the four research questions. The demographic and academic details of the students, the nature of the courses, and information about the enrollments, including the grades earned, were described first.

In an attempt to identify relationships between variables or groups of students, a correlation comparison was completed across multiple variables within the entire study population as well as within the face-to-face and online subsets. To create a prediction model, a logistic regression analysis was completed for the study population as a whole, as well as for both the face-to-face and online subsets.

The next chapter will address each of the research questions and include interpretations of the analysis provided in this chapter. The information on the students, the courses, and the enrollments will be used to provide context for the discussion and interpretation.

CHAPTER 5: DISCUSSION AND CONCLUSIONS

Introduction

The purpose of this study was to identify which demographic, academic, and course related characteristics are most closely related to successful completion of 100 and 200 level courses in both face-to-face and online formats. This chapter will discuss the results of the analysis and make connections between the literature and the findings from the data collected for this study. It will also include suggestions for further research, the significance of the findings, and how the findings can be used.

The following research questions will be used to provide focus for the discussion and make connections between the various analyses described in the previous chapter:

1. Which are important predictors from student characteristics that lead to successful completion of 100 and 200 level classes taken online, as measured by final grade?
2. Which are important predictors from student characteristics that lead to successful completion of 100 and 200 level classes taken face-to-face, as measured by final grade?
3. What predictors are common or differ between online and face-to-face settings?
4. Which academic departments or individual courses can be identified as significant and in need of further analysis?

Demographics and Courses

The demographics of the population used in this study were comparable to the population of the university. Male students appeared to have a preference for face-to-face course enrollments as the percentage of males enrolled in online courses was significantly lower than in the face-to-face courses. There were also differences in enrollments based on age. Based on the data, younger, traditional students appeared to prefer face-to-face courses when given an option. In contrast, there were more students in the older age groups enrolled in online courses. This could be related to the many other competing priorities nontraditional students must balance, including employment and care for dependents (Ewert, 2010; Watt & Wagner, 2016), as opposed to a genuine course modality preference.

The courses included in this study were limited to the 100 and 200 level courses that were offered in both online and face-to-face formats during the two-year period from Fall 2013 through Summer 2015. As can be observed in Table 10, during the traditional school year, which included the fall and spring semesters, approximately 76% of the course sections included in the study were face-to-face courses. During these semesters, the average age of students enrolled in the courses is 21.9 years. This indicates traditional aged students are the majority during the school year. However, in the summer, the balance of face-to-face and online courses shifted such that only 44% of the courses were offered face-to-face. This shift appears to be associated with a common reason that students opt for online courses. Students choose to take online courses for the flexibility of time, location, and pace (Stansfield et al., 2004). Additionally, the average age of the student during summer rose to 24.5 years of age. This implies that nontraditional students work toward completing their education year-round as opposed to only during the school year, while traditional students take the summer off to spend with family or to earn money. This aligns with the research that found nontraditional students tend to take courses that fit their schedule as opposed to conforming to the traditional school year (Daniel, 2000; Watts & Wagner, 2016).

Predictors of Academic Success

This study identified several of the following common success factors in both online and face-to-face environments: gender, ethnicity, age, first generation status, residency status, academic level academic load, the term of enrollment, and primary major college. This finding indicates that these characteristics are predictive of stronger academic performance despite the course format. When considering demographic characteristics, females performed better than male students in course enrollments whether they were face-to-face or online. This finding is in agreement with the studies completed by Aragon & Johnson (2008), Hung et al. (2012), Reason (2003), Valasek (2001), and Yasmin (2013). In general, ethnicity was not a strong predictor. One common finding in this study was that students of Asian descent performed slightly better than all other ethnic groups. This is in alignment with other studies addressing ethnicity completed by Nora et al. (2005), Reason, (2003), and Swail (2004).

Age was challenging to use as a predictive behavior because both older and younger students earned higher average grades than students in the middle age ranges. Studies reviewed in the literature had mixed results based on the use of age as a predictor, so these results match the previous studies. Several studies found younger students were more likely to be successful in their course enrollments (Hung et al, 2012; Osborn, 2001;

Yasmin, 2013), while other studies found older students were more likely to be successful (Muse, 2003; Valasek, 2001). The younger student success is likely due to the number of students enrolled in concurrent enrollment courses while the older students often have a different level of intrinsic motivation for their learning (Stansfield et al., 2004).

Like the studies completed by Choy (2001), Demetriou and Schmitz-Sciborski (2011), and Thayer (2000), this study found that first generation students earned lower grades than their counterparts who are not first generation students. First generation students tend to have lower levels of college readiness and a lack of support from family and friends as compared to students who are not first generation (Falcon, 2015; Stebleton & Soria, 2013). These challenges for first generation students may be real, but sometimes are only perceptions for these students.

Data was not available as to whether students resided on campus or were commuter students, which was found to be an indicator of success in some studies, but students enrolled as nonresidents of the state performed significantly better than residents. Non-resident students are required to pay the higher out-of-state tuition rates. While no information on a correlation between tuition rates and academic success were found in the literature, there were studies that identified a positive relationship between students who received educational grants and academic success (Conrood, 2008). Another explanation for the higher grades from nonresident students is the opportunity for nonresident scholarships. Students who meet minimum GPA (3.6 and above) and entrance exam requirements (ACT 26 or higher, SAT 1240 or higher) from partner states can receive scholarships to cover the difference between nonresident and resident tuition rates (Office of Financial Aid, 2016). If a high level of achievement isnot maintained, students may lose this financial assistance.

One academic factor from this study that contradicts the existing literature is success based on academic load. For the student audience in the study population, students enrolled part-time performed better in both face-to-face and online courses as compared to those enrolled full-time. The literature from other studies consistently found that full-time students were more likely to succeed (Adelman, 1999; Aragon & Johnson, 2008; Colorado & Eberle, 2010; Demetriou & Schmitz-Sciborski, 2011; de Freitas et al., 2015). There are many possible explanations for this finding, but not one identified in the existing literature. One study, completed by Ibrahim, Freeman, and Shelley (2011), evaluated demographic and job satisfaction variables related to the academic success of part-time students. They found that students were more successful in their courses if they were satisfied with their employment and if their job was related to their field of study. Data of this nature was not available for this study.

Another academic factor of interest was a student's high school GPA. This data point was available for only about 80% of the enrollments, there was a very weak correlation between high school GPA and final grade in a course (r = 0.09202, $p <$ 0.0001). While this result aligns with the literature, it is a very weak correlation. It is not nearly as strong as what Bowen, Chingos, and McPherson (2009) concluded when they stated that the high school GPA is one of the best predictors of college graduation. Students need to successfully complete their individual courses to be eligible to graduate. Demetriou and Schmitz-Sciborski (2011) also reported on the connection between high school GPA and success at the university level. The university that was the basis of this study had a mix of traditional and nontraditional students. There were only two fields used in this study that can be used to distinguish traditional from nontraditional students. Those were the age and academic load. Using these two fields to distinguish nontraditional, 8% of the course enrollments were identified as nontraditional. As a result, there were many students who did not begin their higher education directly after high school. That delay is likely to change the level of motivation for students as well as provide time for additional maturity when it comes to study skills and prioritization of schoolwork.

Research Question 1: Which are important predictors from student characteristics that lead to successful completion of 100 and 200 level classes taken online, as measured by final grade?

The overall average final grade for online courses was 2.676 with 79.29% of the students receiving a grade of a C or better. Nearly 40% of students enrolled in online courses finished their courses earning a grade of an A, while 16.51% (*N* = 3,588) earned an F or withdrew from the course. Of those students who received failing grades, approximately 30% opted to withdraw from the class after the add/drop deadline. Based on the logistic regression, overall, demographic factors alone account for slightly more than 2% of student success in online courses. First generation status was the most significant of those factors. Using the odds ratio as a means of comparison, a non-first generation student was 1.194 times more likely to be successful in their online course enrollment than their first generation classmates. This finding corresponds with the studies completed by Choy (2001), Dimetriou and Schmitz-Sciborski (2011), and Thayer (2000). Similar to the study completed by Choy (2001), this study identified that there are many factors in addition to first generation status that influenced a likelihood of success once they decide to enroll. For online courses, one of the more significant factors include the age at course start (older students are more likely to be successful). All factors and their odds ratios are identified in Table 15.

In alignment with the literature (Dupin-Bryant, 2004; Levy, 2007; Muse, 2003; Osborn, 2001), this study verified that the further a student progresses in their academic career, the more likely they are to be successful in their individual courses. One explanation for this finding was that unsuccessful students were more likely to drop out as opposed to returning to school following semesters in which failing grades were earned. This trend was unique to students enrolled in online courses for this study.

The characteristic that was found to be the strongest predictor of success was a student’s cumulative GPA. Ten of the studies cited in Table 1 indicated that a higher cumulative GPA correlates to success in either online or face-to-face courses. One study in particular (Osborn, 2001), found that cumulative GPA is not a strong predictor when analyzed in isolation. In contrast, this study’s findings contradict Osborn’s findings as can be observed in the results of the logistic regression for online courses. The odds ratio for cumulative GPA for online course enrollments shows that for each full point increase in GPA a student is 2.1530 times more likely to pass their online course.

<u>Research Question 2: Which are important predictors from student characteristics that lead to successful completion of 100 and 200 level classes taken face-to-face, as measured by final grade?</u>

The overall final grade average for face-to-face course enrollments was 2.653 with 81.19% of the students receiving a grade of a C or better. Of the students enrolled in face-to-face courses, 34.46% earned a grade of an A. In contrast, 13.41% (*N* = 10,621) earned an F or withdrew from the course. Of those students who received failing grades, approximately 22% opted to withdraw from the class after the add/drop deadline.

One finding that was unique to the face-to-face course enrollments was the relationship between academic level, or the amount of time a student had been attending college, and final grade. For the study population as a whole, the higher the academic level, the higher the final grade average for enrollments, which was in alignment with the literature (Dupin-Bryant, 2004; Levy, 2007; Muse, 2003; Osborn, 2001). This was not the case for the face-to-face course enrollments. For the face-to-face population in this study, freshmen performed better than both sophomores and juniors in the face-to-face course enrollments. Other studies that addressed the relationship between academic level and final grade, including those by Dupin-Bryant (2004), Levy (2007), Muse (2003), and Osborn (2001), focused on a review of online course enrollments as opposed to face-to-face enrollments. One study by Devadoss and Foltz (1996), reported student grades based on the year in college for face-to-face enrollments. Similar to this study, they found that seniors earned the highest grades. However, that is where the similarities end. They reported that sophomores outperformed juniors by a hundredth of a grade point average, but both significantly outperformed freshmen. One explanation for this finding is the high number of concurrently enrolled students. These students earned significantly higher grades than the traditional post-secondary students.

Research Question 3: What predictors are common or differ between online and face-to-face settings?

The mean final grade for face-to-face enrollments was significantly lower than the mean final grade for online enrollments. However, when reducing the variable to two values, successful, A, B, or C, and unsuccessful, D, F, or W, completion of the course enrollment, the results were different. Students in face-to-face course enrollments were more likely to be successful than students enrolled in online courses. A careful review of Figure 4 shows that students in online courses earn more A grades, but also more F grades. In contrast, students in face-to-face courses had a slightly flatter distribution of grades, yet still not a normal curve. While one modality was more successful when considering the weights of letter grades, the other modality performed better when the classification was reduced to a simple successful or not. This implies there was no significant difference based on course modality alone. However, there was a significant difference in the percentage of students who withdrew from online courses after the add/drop deadline. Approximately 30% of the failing grades for online students were attributed to students who withdrew from their course. During the same time, only about 22% of the failing grades for face-to-face students withdrew from their course. This difference may be attributed to a student past educational experiences. Online learning is still a new arena for many students, and the experience may not match their expectations, resulting in a lower level of student satisfaction and a student choosing to withdraw from their online course (Paechter, Maier, & Macher, 2010).

There were differences in the levels of success for students within certain demographic groups. When considering gender, female students in face-to-face course enrollments were successful about 3% more often as compared to females in online courses. However, when looking at the successful completion rate of course enrollments for males, the difference was less than one-tenth of one percent.

When looking at online and face-to-face courses and the age of students enrolled, face-to-face course success was in alignment with the study completed by Nora and Crisp (2012), where younger students were more successful than older students. On the other hand, when looking at only the online courses, older students had higher grades than younger students, which matches the findings in studies completed by Muse (2003) and Valasek (2001). The analysis of student age showed that there were consistent differences in the rate of success between face-to-face and online with the exception of those that were fifty years of age and over at the time of their enrollment. Students age fifty and over were much more successful in face-to-face courses (77.5% pass rate) as compared to online (70.2% pass rate). All other age groups had no more than a 2% variance in the rate of success. This is noteworthy since it was the older age groups that enroll in online courses at a higher rate than their younger counterparts. Although the age at course start was transformed to normalize the distribution, this difference is best seen through the logistic regression and the odds ratio. In the face-to-face courses, the regression coefficient (β) is negative, indicating the older a student is, the less likely they are to be successful. In contrast, in the online courses, the regression coefficient (β) is positive signifying a positive correlation between age and success in an online course.

Although the numbers were small, Pacific Islanders performed significantly better in their online course enrollments as compared to their face-to-face courses. Pacific Islanders were successful in their online courses 82.9% of the time, but were only successful 75.0% of the time in their face-to-face course enrollments. All other ethnic groups had no more than a 2% variance in their success in face-to-face as compared to online course enrollments.

A student's primary degree type and major had an impact on success in their chosen course enrollments. Students working toward a bachelor's degree earned higher grades online as opposed to face-to-face. In contrast, high school student enrolled in college level courses performed better in the face-to-face environment. High school students are successful in face-to-face courses at a rate nearly 10% higher than when taking online courses. The high school students chose face-to-face enrollments over online enrollments much more often. Only 6% of high school enrollments were completed online. One explanation for this result is that high school students likely do not have the same level of choice for course modality as an on campus student. In contrast, students enrolled as part of their work for another type of degree, whether it be for a certificate, an associate's degree, a graduate student taking an undergraduate course, or a student taking courses of interest, all do better online. These students also opted for online courses at a higher rate. Students working toward something other than a bachelor's degree were more likely to be nontraditional students, and therefore have other obligations in addition to their university level courses. Often, these students have a high level of motivation, so are likely to do well in their courses, whether face-to-face or online. Additionally, the students in this study that were working toward another degree type were much more successful when enrolled part-time as opposed to full-time.

The relationship between the GPA earned for the term and the success of the students was evident in both the online and face-to-face enrollments. The correlation between term GPA and success in face-to-face course enrollments was moderately positive ($r = 0.58454$, $p < 0.0001$). There was a strong positive correlation between the term GPA and success in the online enrollments ($r = 0.71856$, $p < 0.0001$). There are concerns about the collinearity of this variable, so it was excluded from regression calculations. Students who were enrolled part-time, taking only a single course, would have a term GPA equal to their course grade.

Research Question 4: Which academic departments or individual courses can be identified as significant and in need of further analysis?

When completing the analysis, students who had high school listed as their primary degree type had significantly higher grades than students who had completed high school. These students were identified as the group in need of further analysis. When comparing these students to the study population as a whole, the rate of success for the high school students was 96.65%. In contrast, their post-secondary counterparts were successful only 80.78% of the time.

Courses offered as concurrent enrollment, or dual credit, courses are designed to meet a number of goals. The courses are college courses, following a university approved syllabus, that is most often taught in the high school by a high school teacher that meets university qualifications (Karp & Hughes, 2008). They help bridge the transition from high school to college education, ensuring college readiness for these students. Additionally, they provide opportunities for high achieving high school students to get a head start on their college education (Hoffmann, 2012).

When analyzing the demographics, there was approximately a 9% higher percentage of females that took courses as concurrent enrollment as compared to the students in the study population. Similarly, there was a slightly higher percentage of Caucasians enrolled through concurrent enrollment, but these factors do not seem to have any relationship with the success of the students. There was a significant difference in the distribution of the colleges offering the courses in which the concurrently enrolled students opted to take, but that appeared to be related to the courses the university and the area high schools offer as a dual credit option as opposed to student choice. Their higher success rate and the higher average final grade can likely be attributed to the fact that they are currently high achieving high school students, and were provided the opportunity to enroll in college level courses because they are often limited to students in college-prep tracks (Karp & Hughes, 2008).

Limitations

Like any purely quantitative study, this study had limitations based on the absence of any qualitative data from the study. Specifically, the students that were included in this study should not be defined by their demographic and academic information alone. There are many other factors that may have influenced student success in either face-to-face or online courses. These factors include motivation, both intrinsic and extrinsic (Stansfield et al., 2004), as well as the student's readiness for the academic rigor of the course. Other aspects of a student's life can interfere with their education, including obligations for work and family and the level of support from the family, friends, and coworkers (Bean & Metzner, 1985; Park & Choi, 2009; Tello, 2007). Many of these factors could have been addressed through a mixed methods study.

The quality of the course experiences related to the data was unknown. Both face-to-face and online courses vary greatly in the quality of the educational experience. These variances may be attributed to the instructor, the curriculum, or other factors. An instructor may have been new to a subject, new to a given course, or their teaching style may not have been a good fit for the student in either face-to-face or online course sections.

A course itself evolves over time. Faculty members will often adjust their course content or instruction from semester to semester hoping it improves the course experience for students. The instructional strategy used in the course can vary greatly from section to section. Often the instructional techniques used in an online class are different than those used in face-to-face courses. These varied teaching strategies may have been beneficial in one learning format for some students yet hurt others in a different format.

Data was collected as to which semester a student enrolled in a course, but the semester that a student chose to enroll may have affected their success. This could be due to a number of factors. For example, a student-athlete might have enrolled in the given course during the semester that practice activities and games needed to fit into the schedule. Seasonal jobs and other commitments could also influence the time a student has to dedicate to school work.

Finally, the student population varies from institution to institution. Kalsbeek and Zucker (2013) argue that a student population is unique to the university, and there needs to be a change in marketing strategies to greatly alter the student population. Therefore, the results of this study were unique to this university, and may not be directly transferable or generalized to other institutions of higher education.

Recommendations for Future Research

This study was a comprehensive quantitative study that focused on learning analytics. There are benefits from additional research that combines both the qualitative and quantitative aspects of this topic. This study evaluated only demographic, academic, and course data and how those factors influence successful completion of a course. The results could be greatly enhanced if paired with research centered around student perceptions and the impact on retention from semester to semester. Analysis of data on student attendance and information from the learning management system would also add value to the university and research community.

Another area that could benefit from more in depth study would be an analysis of who withdraws from courses after the add/drop deadline established by the university. A study of this nature would need to include information gathered from these students as to why they chose to withdraw, and the types of courses that the student chose to drop.

The concurrent enrollment students experienced a much higher level of success in their individual courses. It could benefit the university to track these students beyond high school; identifying which students choose to attend the same university after graduation, or opt to apply to a different university. Additionally, the high schools and the university could benefit from information on how many students that began their college career as a high school student continue and graduate as well as how long it takes them to complete their degrees.

There were some departments where one modality, either online or face-to-face, did significantly better than the other for the classes offered. Additional research on these courses would not focus on the modality of the more successful courses, but instead look at the differences in rigor, instructional design, and assessment techniques used in the course formats. Ideally, research would identify courses in need of improvement and employ best practices to balance courses modalities.

Implications of the Results

This study found that course modality, either face-to-face or online, was not a determining factor of success at the university level, nor were most demographic or academic factors. In some cases, the course itself played a role in the likelihood of a student's success, but the best predictor was a student's previous academic success, as observed through cumulative GPA. This success was either at the high school level, in terms of concurrent enrollment, or at the university level.

One concern was the higher number of withdrawals in the online courses. Despite increased enrollments in online courses, online learning is still a modality that many students have not experienced. Because of this situation, the expectations for courses need to be clearly communicated to students early in the learning experience to enable success. This may help to equalize withdrawals in online courses and bring it closer to the withdrawal rate of face-to-face courses, an area of concern for online course offerings at the university. One misconception that is common among college students is that online courses will be easier, or less rigorous than face-to-face courses. Some students who enroll in online courses may discover this is not necessarily the case upon enrolling in a class and a review of the syllabus and end up withdrawing from the class.

The results of this study can be used by a number of stakeholders both within the university and beyond. The university administrators can draw from this information to alter admissions standards that can affect the likelihood of success in course enrollments, and in turn impact the graduation and retention rates (Dziuban et al., 2012). If the university chooses to grow enrollments, they would lower entrance requirements. If, on the other hand, they want to focus on increased graduation rates, they can use the results of this study to restrict admissions in a manner that encourages success. To do so, they could look at the factors that were indicators of success like entry level GPA. While university cumulative GPA is the greatest predictor of success, other factors can be used in setting the standards.

Faculty and support staff at the university can use the information to identify problematic courses. For example, some departments have significant differences in success rates between the online and face-to-face modalities. The reason for these differences may be due to the design of the courses, or the instructional techniques employed in the course. These courses and instructors can be identified and reviewed by instructional designers for a redesign that can narrow the performance gap (Lockyer, et al., 2013). Some examples include courses offered by the College of Engineering, the communications department, world languages, chemistry and business courses.

Faculty in both face-to-face and online courses can use information on the demographic and academic factors of the students enrolled in their courses to perform some preliminary student analysis. For example, if an instructor learns that most of the students enrolled in their course has work experience and is enrolled on a part-time status, he or she may choose to integrate some of the andragogical techniques outlined by Knowles (1984) such as providing them with opportunities to share their life experiences and apply them to their learning. Academic advising can apply this information in helping students select classes and to inform which students are in need of additional support.

In conclusion, the action that can be taken on the specific results of this study can help universities integrate statistical modeling and other learning analytics techniques into their decision making processes. The type of data included in this study can be combined with learning activity data to advance the analytics to a prescriptive level. As the field of learning analytics continues to grow, universities will find these tools to be an invaluable resource for advising students and making informed decisions at all levels within the university.

This research was conducted under approval from the Institutional Review Board at Boise State University, protocol #104-SB16-102.

REFERENCES

Adelman, C. (1999). *Answers in the tool box: Academic intensity, attendance patterns, and bachelor's degree attainment.* Washington D. C.: Office of Education Research and Improvements, U. S. Department of Education.

Affendey, L. S., Paris, I. H. M., Mustapha, N., Sulaiman, M. N., & Muda, Z. (2010). Ranking of influencing factors in predicting students' academic performance. *Information Technology Journal, 9*(4), 832-837.

Allen, I. E., & Seaman, J. (2016). *Online report card: Tracking Online Education in the United States*. Babson Park, MA. Retrieved from http://onlinelearningsurvey.com/reports/onlinereportcard.pdf

Aragon, S. R., & Johnson, E. S. (2008). Factors influencing completion and noncompletion of community college online courses. *American Journal of Distance Education*, *22*(3), 146–158. http://doi.org/10.1080/08923640802239962

Astin, A. W. (1975). *Preventing students from dropping out.* San Francisco, CA: Jossey-Bass.

Baker, B. M. (2007). *A conceptual* framework *for making knowledge actionable through capital formation* (Order No. 3254328). Available from ProQuest Dissertations & Theses Global. (304704280).

Baker, R., & Siemens, G. (2014) Educational data mining and learning analytics. In Sawyer, K. (Ed.) *Cambridge Handbook of the Learning Sciences: 2nd Edition*, pp. 253-274. Retrieved from: http://www.columbia.edu/~rsb2162/BakerSiemensHandbook2013.pdf

Baum, S., Ma, J., & Payea, K. (2013). *Education pays 2013: The benefits of higher education for individuals and society*. New York, NY: College Board. Retrieved from: https://trends.collegeboard.org/sites/default/files/education-pays-2013-full-report.pdf

Bean, J. P. (2005). Nine themes of college student retention. In A. Seidman (Ed.) *College Student Retention* (pp. 215-244). Westport, CT: American Council on Education and Praeger Publishers.

Bean, J. P., & Metzner, B. S. (1985). A conceptual model of nontraditional undergraduate attrition. *Review of Educational Research*, *55*(4), 485-540.

Becker, B. (2013). Learning analytics: Insights into the natural learning behavior of our students. *Behavioral and Social Sciences Librarian 32*(1) 63-67. Doi: 10.1080/01639269.2013.751804

Berger, J. B., & Lyon, S. C. (2005). Past to present: A historical look at retention. In A. Seidman (Ed.) *College Student Retention* (pp. 1-29). Westport, CT: American Council on Education and Praeger Publishers.

Bok, D. (2013). *Higher education in America.* Princeton, NJ: Princeton University Press.

Bowen, W. G., Chingos, M. M., & McPherson, M. S. (2009). *Crossing the finish line: Completing college at America's public universities*. Princeton, NJ: Princeton University Press.

Braxton, J. M., & Hirschy, A. S. (2005). Theoretical developments in the study of college student departure. In A. Seidman (Ed.) *College Student Retention* (pp. 61-87). Westport, CT: American Council on Education and Praeger Publishers.

Brown, M. (2011). Learning Analytics: The coming third wave. *EDUCAUSE Learning Initiative Brief*, 1–4. Retrieved from https://net.educause.edu/ir/library/pdf/ELIB1101.pdf

Campbell, J. P., deBlois, P., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new era, *EDUCAUSE Review*, *42*(4), 40-57.

Campbell, J. P. & Oblinger, D. G. (2007). *Academic analytics.* EDUCAUSE Whitepaper. 1-24. Retrieved from http://net.educause.edu/ir/library/pdf/PUB6101.pdf

Choy, S. (2001). *Students whose parents did not go to college: Postsecondary access, persistence, and attainment*, (NCES Publication No. 2001–126). Retrieved from National Center for Educational Statistics: http://nces.ed.gov/pubs2001/2001126.pdf

Clark, R. E. (1983). Reconsidering research on learning from media. In R. E. Clark (Ed.), *Learning from Media* (pp. 1-12). Charlotte, NC: Information Age Publishing.

Colorado, J. T., & Eberle, J. (2010). Student demographics and success in online learning environments. *Emporia State Research Studies, 46*(1), 4–10.

Conrood, L. (2008). The effects of financial aid amounts on academic performance. *The Park Place Economist, 16*(1), 24-35.

Cortes, C. M. (2013). Profile in action: Linking admission and retention. *New Directions for Higher Education, 2013*(161), 59-69.

Daniel, E. L. (2000). A review of time-shortened courses across disciplines. *College Student Journal, 34*(2).

de Freitas, S., Gibson, D., DuPlessis, C., Halloran, P., Williams, E., Ambrose, M., Dunwell, I., Arnab, S. (2015). Foundations of dynamic learning analytics: Using university student data to increase retention. *British Journal of Educational Technology, 46*(6), 1175-1188.

Demetriou, C., & Schmitz-Sciborski, A. (2011). Integration, motivation, strengths, and optimism: Retention theories past, present, and future. In R. Hayes (Ed.), *Proceedings of the 7th National Symposium on Student Retention, 2011, Charleston.* (pp.300-312). Norman, OK: The University of Oklahoma.

Devadoss, S., & Foltz, J. (1996). Evaluation of factors influencing student class attendance and performance. *American Journal of Agricultural Economics, 78*(3), 499-507. Retrieved from http://www.jstor.org/stable/1243268

Dringus, L. P. (2011). Learning Analytics Considered Harmful. *Journal of Asynchronous Learning Networks*, *16*(3), 87–101.

Dron, J., & Anderson, T. (2009). *On the design of collective applications.* Proceedings of the International Conference on Computational Science and Engineering, Vol 4, pp. 368-374. Retrieved from http://hdl.handle.net/2149/2305

Dupin-Bryant, P. (2004). Pre-entry variables related to retention in online distance education. *American Journal of Distance Education, 18*(4), 199-206.

Dziuban, C., Moskal, P., Cavanagh, T., & Watts, A. (2012). Analytics that inform the university: Using data you already have. *Journal of Asynchronous Learning Network*, *16*(3), 21–38.

eCampus Center, Extended Studies. (2015). *Boise State eCampus Snapshot 2015* [Fact sheet]. Retrieved from http://ecampus.boisestate.edu/wp-content/uploads/2015/06/2014-2015-eCampusSnapshot.pdf

Elias, T. (2011). *Learning analytics: Definitions, Processes, and Potential.* Retrieved from: http://learninganalytics.net/LearningAnalyticsDefinitionsProcessesPotential.pdf

Ewert, S. (2010). Male and female pathways through four-year colleges: Disruption and sex stratification in higher education. *American Educational Research Journal*, *47*(4), 744-773.

Falcon, L. (2015). Breaking down barriers: First-generation college students and college success. *Innovation*, *10*(6). Retrieved from: https://www.league.org/innovation-showcase/breaking-down-barriers-first-generation-college-students-and-college-success

Geiger, R. L. (2015). The history of American higher education: Learning and culture from the founding to World War II. Princeton, NJ: Princeton University Press.

Grebennikov, L., & Skaines, I. (2009). Gender and higher education experience: A case study. *Higher Education Research and Development, 29*(1), 71-84. doi: 10.1080/07294360802444370

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Educational Technology and Society, 15*(3), 42-57.

Habley, W. R., Bloom, J. L., Robbins, S., & Gore, P. A. (2012). *Increasing persistence: Research-based strategies for college student success.* Hoboken, NJ: John Wiley & Sons.

Hand, D. J. (1998). Data mining: Statistics and more? *The American Statistician, 52*(2), 112-118.

Harrell, I. L., & Bower, B. L. (2011). Student characteristics that predict persistence in community college online courses. *American Journal of Distance Education, 25*(3), 178–191. doi: 10.1080/08923647.2011.590107

Hart, C. (2012). Factors associated with student persistence in an online program of study: A review of the literature. *Journal of Interactive Online Learning, 11*(1), 19-42.

Hofmann, E. (2012), Why dual enrollment? *New Directions for Higher Education, 2012*(158), 1–8. doi:10.1002/he.20009

Hofstede, G. H. (2001). Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations. Thousand Oaks, CA: Sage Publications.

Holder, B. (2007). An investigation of hope, academics, environment, and motivation as predictors of persistence in higher education online programs. *The Internet and Higher Education, 10*(2007), 245-260. doi: 10.1016/j.iheduc.2007.08.002

Hung, J. L., Hsu, Y. C., & Rice, K. (2012). Integrating data mining in program evaluation of K-12 online education. *Educational Technology and Society, 15*(3), 27-41.

Ibrahim, N., Freeman, S. A., & Shelley, M. C. (2011). Identifying predictors of academic success for part-tie students at polytechnic institutes in Malaysia. *International Journal of Adult Vocational Education and Technology, 2* (4), 1-16.

Ishler, J. L. C., & Upcraft, M. L. (2004). The keys to first-year student persistence. In M. L. Upcraft, J. N. Gardner, & B. O. Barefoot (Eds.) *Challenging and Supporting the First –Year Student: A Handbook for Improving the First Year of College* (pp. 27-46). Indianapolis, IN: Jossey-Bass.

Ivankova, N. V., & Stick, S. L. (2007). Students' persistence in a distributed doctoral program in educational leadership in higher education: A mixed method study. *Research in Higher Education, 48*(1), 93-135.

Jayaprakash, S. M., Moody, E. W., Laura, E. J., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics, 1*(1), 6-47.

Kalsbeek, D. H., & Zucker, B. (2013). Reframing retention strategy: A focus on profile. *New Directions for Higher Education, 2013*(161), 15-25. doi: 10.1002/he.20042

Kamens, D. H. (1971). The college charter and college size: Effects on occupational choice and college attrition. *Sociology of Education, 44*(3), 270-296.

Karp, M. M., & Hughes, K. L. (2008). Dual enrollment can benefit a broad range of students. *Techniques: Connecting Education and Careers, 83*(7), 14-17.

Kemp, W. C. (2002). Persistence of adult learners in distance education. *American Journal of Distance Education, 16*(2), 65.

King, A. (1993). From sage on the stage to guide on the side. *College Teaching, 41*(1), 30.

Knowles, M. S. (1984). Andragogy in action: Applying modern principles of adult learning. San Francisco, CA: Jossey-Bass.

Lee, Y., & Choi, J. (2011). A review of online course dropout research: Implications for practice and future research. *Educational Technology Research and Development, 59.* 593-618.

Levy, Y. (2007). Comparing dropouts and persistence in e-learning courses. *Computers and Education, 48*(2), 185-204.

Liu, S. Y., Gomez, J., & Yen, C. (2009). Community college online course retention and final grade: Predictability of social presence. *Journal of Interactive Online Learning, 8*(2), 165-182.

Lockee, B. B., Burton, J. K., & Cross, L. H. (1999). No comparison: Distance education finds a new use for 'no significant difference'. *Educational Technology, Research and Development, 47*(3), 33-42.

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist, 57*(10), 1439-1459.

Lotsari, E., Verykios, V. S., Panagiotakopoulos, C., & Kalles, D. (2014). A learning analytics methodology for student profiling. *Lecture Notes in Computer Science, 8445*(2014), 300-312.

Martin, T., & Sherin, B. (2013). Learning analytics and computational techniques for detecting and evaluating patterns in learning: An introduction to the special issue. *Journal of the Learning Sciences, 22*(4), 511-520. doi: 10.1080/10508406.2013.840466

McKenzie, K., & Schweitzer, R. (2001). Who succeeds at university? Factors predicting academic performance in first year Australian university students. *Higher Education Research and Development, 20*(1), 21-33. doi: 10.1080/07924360120043621

Menager-Beeley, R. (2001). Student success in web based distance learning: Measuring motivation to identify at risk students and improve retention in online classes. (Report No. 466608). Orlando, FL: World Conference on the WWW and Internet Proceedings. Retrieved from ERIC Database.

Moore, M. G., & Kearsley, G. (2005). *Distance education: A systems view* (2nd ed.). Belmont, CA: Thomson Wadsworth.

Morris, J. E. (n.d.). Cultural expectations and student learning. *Education Encyclopedia.* Retrieved from: http://education.stateuniversity.com/pages/2346/Race-Ethnicity-Culture.html

Morris, L. V., Wu, S.-S., & Finnegan, C. L. (2005). Predicting retention in online general education courses. *The American Journal of Distance Education, 19*(1), 23-26.

Müller, T. (2008). Persistence of women in online degree-completion programs. *International Review of Research in Open and Distance Learning, 9*(2), 1-18.

Muse, H. E. (2003). The web-based community college student: An examination of factors that lead to success and risk. *The Internet and Higher Education, 6*(2003), 241-261. doi: 10.1016/S1096-7516-(03)00044-7

National Center for Education Statistics. (2014a). *Digest of Education Statistics, 2013* (NCES Table No. 326.30). Retrieved from http://nces.ed.gov/programs/digest/d13/tables/dt13_326.30.asp

National Center for Educational Statistics (2014b). *Enrollment in distance education courses, by state: Fall 2012* (NCES Publication No. 2014023). Retrieved from http://nces.ed.gov/pubs2014/2014023.pdf

National Center for Education Statistics. (2015). *Digest of Education Statistics, 2013* (NCES Table No. 330.10). Retrieved from https://nces.ed.gov/programs/digest/d13/tables/dt13_330.10.asp

Nelson, G. S. (2015). *Practical implications of sharing data: A primer on data privacy, anonymization, and de-identification.* [White paper]. Retrieved from http://support.sas.com/resources/papers/proceedings15/1884-2015.pdf.

Nora, A., Barlow, E., Crisp, G. (2005). Student persistence and degree attainment beyond the first year in college. In A. Seidman (Ed.) College Student Retention (pp. 129-

Oblinger, D. G. (2012). Let's talk analytics. *EDUCAUSE Review, 47*(4), 10-13.

Office of Communications and Marketing. (2014). *Facts and figures 2014-2015* Retrieved from http://scholarworks.boisestate.edu/facts_figs/22

Office of Financial Aid. (2016). *Nonresident scholarship programs.* Retrieved from https://financialaid.boisestate.edu/scholarships/non-resident-tuition-assistance-programs/

Office of Institutional Research, Boise State University. (2013). *Retention, persistence, and graduation rates summary.* Retrieved from http://ir.boisestate.edu/wp-content/uploads/2014/04/Ret-persistence-grad-rates-updated-10.1.13-REV.pdf

Office of the Provost, Boise State University. (2012). *Focus on effectiveness: Boise State University's strategic plan for 2012-2017.* Retrieved from http://academics.boisestate.edu/strategic-plan/

Osborn, V. (2001). Identifying at-risk students in videoconferencing and web-based distance education. *American Journal of Distance Education, 15*(1), 41-54.

Paechter, M., Maier, B., & Macher, D. (2010). Student's expectations of, and their experiences in e-learning: Their relation to learning achievements and course satisfaction. *Computers and Education*, *54*(1), 222-229.

Pardo, A. (2014). Designing learning analytics experiences. In J. A. Larusson & B. White (Eds.) *Learning analytics: From research to practice* (pp. 15-38). New York, NY: Springer.

Park, J.-H., & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Educational Technology and Society, 12*(4), 207-217.

Patterson, B., & McFadden, C. (2009). Attrition in online campus degree programs. *Online Journal of Distance Learning Administration*, *12*(2). Retrieved from http://www.westga.edu/~distance/ojdla/summer122/patterson112.html

Peng, C-Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *Journal of Educational Research, 96* (1), 3-14. doi: 10.1080/00220670209598786

Picciano, A. G. (2012). The evolution of big data and learning analytics in American higher education. *Journal of Asynchronous Learning Networks*, *16*(3), 9-20.

Pontes, M. C. F., Hasit, C., Pontes, N. M. H., Lewis, P. A., & Siefring, K. T. (2010). Variables related to undergraduate student preferences for distance education classes. *Online Journal of Distance Learning Administration, 8*(2). Retrieved from http://www.westga.edu/~distance/ojdla/summer132/pontes_pontes132.html

Reason, R. D. (2003). Student variable that predict retention: Recent research and new developments. *NASPA Journal* (*National Association of Student Personnel Administrators), 40*(4), 172-191.

Reyes, J. A. (2015). The skinny on big data in education: Learning analytics simplified. *Tech Trends*, *59*(2), 75-79.

Richardson, J. E. (2012). Face-to-face versus online tuition: Preference, performance and pass rates in white and ethnic minority students, *British Journal of Educational Technology, 43*(1), 17-27. doi: 10.1111/j.1467-8535.2010.01147.x

Rovai, A. P., Ponton, M. K., & Baker, J. D. (2008). Distance learning in higher education: A programmatic approach to planning, design, instruction, evaluation, and accreditation. New York, NY: Teachers College Press.

Shelton, B. E., Hung, J-L., & Baughman, S. (2015). Online graduate teacher education: Establishing an EKG for student success intervention. *Technology, Knowledge, and Learning, 20*(1) doi: 10.1007/s10758-015-9254-8

Sher, S. (2013). Teaching value issues in china to chinese students enrolled in american universities. (M. Goldman, Ed.) *Teaching Philosophy*, *36*(4), 373–397. doi:10.5840/teachphil20131014

Siemens, G., & Baker, R. (2012). Learning analytics and educational data mining: Towards communication and collaboration. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*. Retrieved from http://www.columbia.edu/~rsb2162/LAKs%20reformatting%20v2.pdf

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510-1529. doi: 10.1177/0002764213479366

Snyder, T. D. (1993). *120 Years of American education: A statistical portrait* (NCES Publication No. 93442). Retrieved from National Center for Educational Statistics: http://nces.ed.gov/pubs93/93442.pdf

Spady, W. (1970). Dropouts from higher education: An interdisciplinary review and synthesis. *Interchange: A Quarterly Review of Education, 1*(1), 64-85.

Stansfield, M., McLellan, E., & Connolly, T. (2004). Enhancing student performance in online learning and traditional face-to-face delivery. *Journal of Information Technology Education, 3*, 173-188.

Stebleton, M. J. & Soria, K. M. (2013). Breaking down barriers: Academic obstacles of first-generation students at research universities. *The Learning Assistance Review*. Retrieved from the University of Minnesota Digital Conservancy, http://hdl.handle.net/11299/150031.

Swail, W. S. (2004). The art of student retention: A handbook for practitioners and administrators. Austin, TX: Educational Policy Institute.

Tello, S. F. (2007). An analysis of student persistence in online education. *International Journal of Information and Communication Technology Education,3*(3), 47-62.

Thayer, P. B. (2000). Retention of students from first generation and low-income backgrounds (Report No. 446633). Washington D. C.: Department of Education. Retrieved from ERIC Database.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *A Review of Educational Research, 45*(1), 89-125.

U.S. Bureau of Labor Statistics, Office of Occupational Statistics and Employment Projections. (2015). *Earnings and unemployment rates by educational attainment.* Retrieved from: http://www.bls.gov/emp/ep_chart_001.htm

U.S. Department of Education, Office of Educational Technology. (2012). *Enhancing teaching and learning through educational data mining and learning analytics: An issue brief*. Washington, D.C.: U.S. Department of Education.

Valasek, T. (2001). Student persistence in web-based courses: Identifying a profile for success. (Report No. 466276). Branchburg, NJ: Raritan Valley Community College. Retrieved from ERIC Database.

Verbert, K. Manouselis, N., Drachsler, H., & Duval, E. (2012). Dataset-driven research to support learning and knowledge analytics. *Education Technology and Society, 15*(3), 133-148.

Wagner, E., & Ice, P. (2012). Data changes everything: Delivering on the promise of learning analytics in higher education. *EDUCAUSE Review, 47*(4), 32-42.

Wang, Y. A., & Newlin, M. H. (2002). Predictors of performance in the virtual classroom: Identifying and helping at-risk cyber-students. *THE Journal*, *29*(10), 21.

Watt, C., & Wagner, E. (2016). *Improving Post-Traditional Student Success.* Retrieved from https://www.hobsons.com/res/Whitepapers/PostTraditionalStudents_ParFramework_February2016.pdf

Yasmin, J. (2013). Application of the classification tree model in predicting learner dropout behavior in open and distance learning. *Distance Education, 34*(2), 218-231.