View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by Syracuse University Research Facility and Collaborative Environment

Syracuse University

SURFACE

Dissertations - ALL

SURFACE

December 2015

STUDENT CHARACTERISTICS THAT PREDICT PERSISTENCE AND PERFORMANCE IN ONLINE COURSES AND THE FACE-TO-FACE EQUIVALENTS AT A FOUR-YEAR PRIVATE NORTHEASTERN UNIVERSITY

Karen Zannini Bull
Syracuse University

Follow this and additional works at: https://surface.syr.edu/etd

Part of the Education Commons

Recommended Citation

Bull, Karen Zannini, "STUDENT CHARACTERISTICS THAT PREDICT PERSISTENCE AND PERFORMANCE IN ONLINE COURSES AND THE FACE-TO-FACE EQUIVALENTS AT A FOUR-YEAR PRIVATE NORTHEASTERN UNIVERSITY" (2015). *Dissertations - ALL*. 380.
https://surface.syr.edu/etd/380

This Dissertation is brought to you for free and open access by the SURFACE at SURFACE. It has been accepted for inclusion in Dissertations - ALL by an authorized administrator of SURFACE. For more information, please contact surface@syr.edu.

ABSTRACT

Attrition in online courses is of growing concern in higher education. Many researchers and practitioners are concerned about student persistence (course completion) and performance (completion of a course with a grade of C or better) in online courses. This study investigated the undergraduate student characteristics that predict student persistence and performance in online courses and the face-to-face equivalents at a four-year private northeastern university. The sample consists of undergraduate students (42,280 observations, 25,167 unduplicated student headcount, which is the actual number of individual students in the population) who enrolled in courses, regardless of delivery format, from fall 2002 to spring 2013. This study attempted to identify the undergraduate student characteristics that predict student persistence and performance in online courses and the face-to-face equivalents while controlling for all available institutional variables such as demographics (age, gender, race/ethnicity, and financial aid) and academic performance (grade point average prior to enrollment at the institution, concurrent enrollment programs, and math and verbal scholastic aptitude test scores). The student characteristics were examined using multilevel modeling. The first level of analysis was the individual student and the second level of analysis was the academic school/college in which the student was enrolled. The findings of this study were mixed. No cause and effect claims were made. Aligning with much of the literature in this area, the results of this study consistently demonstrate that GPA prior to enrollment at the institution predicts student success in both online courses and the face-to-face equivalents. Students enrolled in the College of Engineering and Computer Science and the School of Management were more likely to succeed (persist and perform) in both online courses and the face-to-face equivalent. Consistently those students who identified their race/ethnicity as a minority, were less likely to succeed in online courses and the face-to-face equivalents.

Keywords: **Course Persistence, Course Performance, Multilevel Modeling, Online Courses, Student Characteristics, Distance Education, Predictor Variables, Undergraduate Students**

STUDENT CHARACTERISTICS THAT PREDICT PERSISTENCE AND PERFORMANCE
IN ONLINE COURSES AND THE FACE-TO-FACE EQUIVALENTS
AT A FOUR-YEAR PRIVATE NORTHEASTERN UNIVERSITY

by

Karen Zannini Bull
B.S. Allegheny College, 2003
M.S. University of Maine, 2005

DISSERTATION

Submitted in partial fulfillment of the requirements for the
degree of Doctor of Philosophy in Instructional Design, Development and Evaluation

Syracuse University
December 2015

Copyright © Karen Zannini Bull 2015

All Rights Reserved

ACKNOWLEDGEMENTS

It has been a long journey but I could not have traveled this road without the support of family, colleagues, and friends.

My greatest appreciation is directed to Dr. Tiffany A. Koszalka for her support as I worked to complete my dissertation. She offered me great guidance and exceptional examples of how to proceed with this process. For that I am grateful. Additionally, I would like to offer Dr. Nick Smith my gratitude for sticking with me for years and preparing me to succeed in the development of my dissertation.

I would like to thank Dr. Kalpana Srinivas and Dr. Yildiray Yildirim for their invaluable feedback, unwavering belief in me, and kind encouragement during my dissertation. I often felt as though they were my shining lights when the skies were cloudy.

To my parents—there are truly no words. I can only say that this degree is for you both. David, my husband, supported me through this roller coaster ride and not once doubted my ability to complete the task. I also want to thank Audrey Burian. Without her humor, perspective on reality, and unwavering support, I would not have been able to stay grounded throughout this process.

Finally, it is true that “it takes a village.” I would like to thank Dr. Geraldine N. de Berly, Dr. Jerry Edmonds, Dr. Rob Pusch, Dr. James Bellini, Dr. Jeffrey Stanton, Dr. John Prusch, Dr. Robert Crocker, Timothy Wasserman, Leigh Tolley, Tiffany Squires, and Micah Shippee.

Table of Contents

List of Figures

List of Tables

CHAPTER 1: INTRODUCTION

Problem statement

Attrition (dropping out) in online courses is of growing concern in higher education. Approximately 62.4% of higher education institutions offer at least one online program, an increase of 35% since 2002 (Allen & Seaman, 2011). The rapid growth of enrollment in online courses has increased the need for research to understand why some students show persistence (completing a course) and performance (earning a grade of C or better) and others do not. This study attempted to determine the characteristics that predict student persistence and performance in online courses and in the face-to-face equivalents at a four-year private northeastern university.

High course attrition rates present major challenges (Gibson, 1996; Carr, 2000; Osborne, 2001). These rates are 10 to 20% higher for online courses than for traditional, face-to-face courses (Carr, 2000; Diaz & Bontenbal, 2001; Dunagan, 2005; Frankola, 2001; Holder, 2007; Lynch 2001; Moody, 2004; Street, 2010; Terry 2001). Yet little is known about the variables that predict student success (persistence and performance) associated with online courses (Frankola, 2001).

It is important to examine these variables. First, online enrollments have grown rapidly and continue to see growth (Allen & Seaman, 2013). Next, the researcher has held two positions at two different institutions in an office of online education, responsible for aiding faculty in course conversion from the face-to-face environment to the online environment. In these roles, faculty have anectdotially reported that they believe that course attrition is higher in their online courses than in their face-to-face courses.

I undertook a study of these variables among undergraduates at a four-year private northeastern university. Using multilevel modeling (MLM), I controlled for many independent demographic and academic-performance variables. Previous research suggests that relationships between variables under these categories may predict student persistence and performance in online courses and the face-to-face equivalents. Demographic variables include age (P. B. Moore 2001; Valasek 2001), gender (Aragon & Johnson, 2008; Valasek, 2001), race/ethnicity (K. Moore, Bartkovich, Fetzner, & Sherrill, 2002; P. B. Moore, 2001; Sullivan, 2001), and financial need (Parker, 2003; Morris, Finnegan, & Wu, 2005; Aragon & Johnson, 2008). Academic performance variables include college grade point average (GPA) (Dupin-Bryant, 2004; Morris, Finnegan, & Wu 2005; Aragon & Johnson, 2008), scholastic aptitude test (SAT) test scores (Morris, Finnegan, & Wu, 2005; Lowenthal, 2014), and participation in concurrent enrollment programs for undergraduate students. A more detailed explanation of independent variable selection will follow in Chapter 2.

Introduction

The widespread use of computers and the Internet have made online learning more accessible to higher education institutions. Today higher education institutions take advantage of these technologies to deliver courses for both undergraduate and graduate programs online. The increased access to technology in homes has enabled online courses to explode, with over 6.1 million students taking at least one online course during the fall 2010 term (Allen & Seaman, 2011). Along with this growth there has been increasing concern about student persistence and performance in these courses (Street, 2010; Twigg, 2009).

According to a 2011 survey of more than 2,500 nonprofit and for-profit colleges and universities conducted by the College Board and the Babson Survey Research Group, the number of college students enrolled in at least one online course increased in 2009 for the 9th straight year (Allen & Seaman, 2011). Thirty-one percent of higher education students—now more than 6.1 million students—take at least one online course; and the rate of growth in online course enrollments is 10 times the rate of all higher education (Allen & Seaman, 2011). The rate continues to increase, so that by the year 2015 postsecondary online enrollments are expected to reach 37% (History of Distance & Online Education Infographic, 2014).

In September 2010 the U.S. Department of Education published a meta-analysis that included a systematic search of the research literature from 1996 through July 2008. The search identified more than a thousand empirical studies of online learning. The study reports that no experimental or controlled quasiexperimental studies had been conducted or published between 1996 through 2006 that compared the learning effectiveness of online and face-to-face instruction (U.S. Department of Education et al., 2010).

The study also reports that students in online conditions performed modestly better, on average, than those learning the same material through traditional face-to-face instruction. Learning outcomes for students who engaged in online learning exceeded those of students receiving face-to-face instruction, with an average effect size of +0.20 favoring online conditions (U.S. Department of Education et al., 2010, p. xiv). The report cautions that

> interpretations of this result . . . should take into consideration the fact that online and face-to-face conditions generally differed on multiple dimensions. This includes the amount of time that learners spent on tasks. The advantages observed for online learning conditions therefore may be the product of aspects of those treatment conditions other than the instructional delivery medium per se.” (U.S. Department of Education et al., 2010, p. xiv)

Some studies note that attrition rates are often 10 to 20% higher for online courses than for traditional, face-to-face courses (Carr, 2000; Diaz & Bontenbal, 2001; Dunagan, 2005; Frankola, 2001; Holder, 2007; Lynch 2001; Moody, 2004; Street, 2010; Terry 2001). Levy (2007), in a review of the literature, reports that attrition rate estimates for online courses range from 25 to 60%. Although there is a lack of consensus regarding the rates of attrition in online courses, based on the number of studies that have been conducted on learners' persistence, it is clear that researchers have identified attrition as a growing concern for the academic community (Lim, 2001). In addition, there is a lack of understanding of the variables that help predict student persistence and performance in online courses.

The multilevel modeling design was selected for this study because of its suitability for the questions being asked (see section titled Research Questions below) and because the existing data set for participants is organized and grouped at more than one level. Figure 1 provides a visual representation of the MLM nested levels.

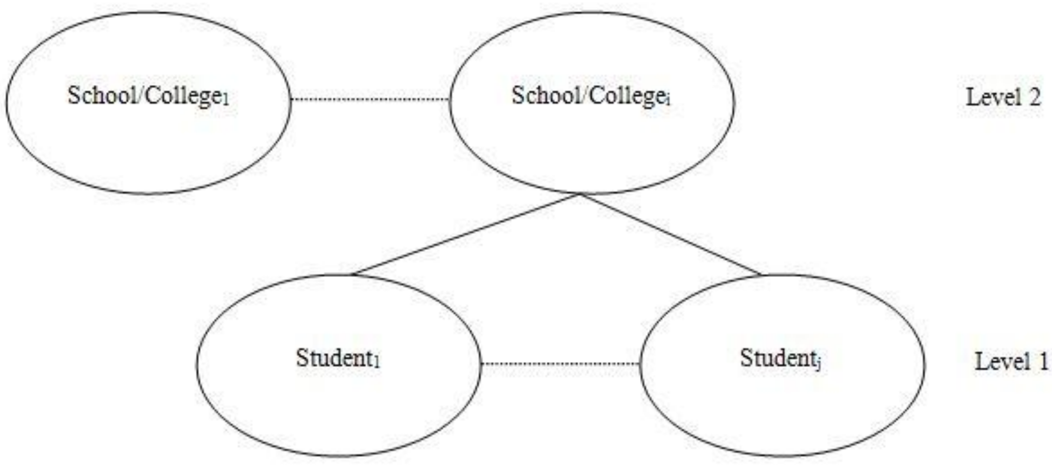

Figure 1. Multilevel Modeling Nested Levels

When a student enrolls at an institution, s/he enrolls in an academic school/college, represented as level 2 in Figure 1. Each academic school/college is comprised of students, represented as level 1 in Figure 1. The units of analysis are individual students who are nested within a contextual/aggregate unit. The contextual/aggregate unit for this study was the academic school/college in which the student is enrolled. The present study also includes two levels: the first-level unit is the individual student, who is clustered or nested in the second-level unit, which is the academic school/college. Through this model, the student characteristics that may predict student persistence and performance in online courses and the face-to-face equivalents can be identified.

Purpose of the Study

The purpose of this study was to identify the student characteristics that predict student persistence and performance in online courses and the face-to-face course equivalents while controlling for many independent demographic and academic-performance variables.

In this study, equivalent does not imply a comparison study. If a course was offered online, then the face-to-face course equivalent was also examined. For example, if *introduction to basketweaving 101* was offered in the online format and was also offered in the face-to-face format, then it was included in this study. It is important to caution researchers against conducting a comparison study of persistence and performance between online and face-to-face courses. Since the different delivery versions may include different but equal (or not) types of activities, assessments, and interactions, comparisons of persistence and performance would be like comparing apples to oranges. They will not be meaningful. The data about persistence and performance in each format however are are importrant in teasing out student characteristics that are predictive of each individual format. In the end, patterns that may emerge from these data may be important to designing instruction in one or the other format. More analysis of the actual design of instruction across two platforms will need to be done to complete a ‘comparison study.’ That was not the goal of this work.

The study examined two groups: (a) undergraduate students who had participated in online courses offered by a four-year private northeastern university, and (b) undergraduate students at the same university who had participated in face-to-face course equivalents (the same courses, but offered in a face-to-face format).

Data for the study were extracted and queried from that university’s student record system (SRS). I analyzed the data set by listing and defining all the independent and dependent variables, conducting a descriptive statistics analysis to identify the basic features of the students who had participated in online courses and their face-to-face equivalents, and applying MLM statistical analysis to identify the variables that predict student persistence and performance in these courses.

Research Questions

These are the study’s research questions:

1. Which undergraduate student characteristics (persistence and performance) best predict student success in online courses?
2. Which undergraduate student characteristics (persistence and performance) best predict student success in face-to-face courses?
3. Is there a difference between the characteristics of undergraduate students who successfully complete (persist) online courses and the characteristics of those whose performance is passing (perform)?

4. Is there a difference between the characteristics of undergraduate students who successfully complete face-to-face courses (persist) and the characteristics of those whose performance is passing (perform)?

Due to the binary nature of the outcome variables in this study, it is necessary to point out that the multilevel logistic regression modeling will be employed (Morgan, Leech, Gloeckner, & Barrett, 2013). The log odds of the outcomes are modeled as a linear combination of the predictor variables when the data are clustered or there are both fixed and random effects, as will be implemented in this study (Goldstein, 2011). The appropriate approach to analyzing the data set of this study is based on nested sources of data which come from different levels of hierarchy (in this study, level 1 is the student and level 2 is the academic school/college) (Goldstein, 2011). When the variance of the residual errors is correlated between individual observations as a result of these nested structures, traditional logistic regression is an inappropriate method to employ (Goldstein, 2011).

Motivation for the Study

Online education, which provides access to education for countless individuals, has become an integral part of the mission of higher education institutions in the United States, (Allen & Seaman, 2011). The rapid growth of enrollment in online courses has presented a need for research to determine the characteristics of students who persist and students who do not persist in online courses (Aragon & Johnson, 2008). As online courses continue to be developed, many educators agree that online-course attrition presents major challenges (U.S. Department of Education et al., 2010). Despite awareness of attrition as an issue at both the national and local levels, course attrition rates for online courses tend to be higher than for face-to-face course equivalents. There have been few studies conducted on the variables that predict student success (persistence and performance) in online courses (Aragon & Johnson, 2008; Frankola, 2001). This study aimed to identify the student characteristics that predict student success (persistence and performance) with online courses and the face-to-face equivalents; however, it did not address the issue of why students drop out of or persist in online courses and the face-to-face equivalents.

Conceptual Framework

This study references Kember's (1995) validated model of student progress in distance education. Kember's (1995) model integrates many diverse elements of the field of online education and explains the interrelationships between learners and their context, learning and instruction, organization and context, and culture and policy. This model will serve as a building block to guide this study (see Figure 2).

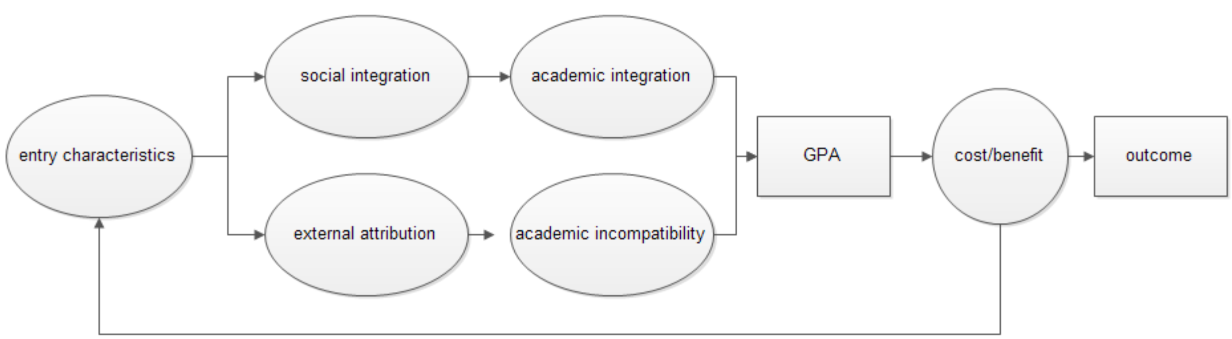

Figure 2. ***Kember's (1995) model of student progress in distance education*** **(p. 2).**

Kember (1995) conducted two studies (an initial and a replication study) to validate the student progress in distance education model. Upon the conclusion of the replication study, Kember (1995) deduced that there was sufficient similarity between the 2 path models generated to confirm the findings of the initial study. There was triangulation between the quantitative and qualitative data, which added to the credibility of the model; therefore, the model could, with reasonable confidence, "be used to make predictions and derive implications for practice" (Kember, 1995, p. 155).

Kember’s model (1995) shows that students enter an online course with a number of predetermined personal traits. Based on these traits, students follow one of two tracks in the model. It is suggested that those students who are able to integrate socially and academically take the positive path in the model (Kember, 1995). Those students who have difficulty achieving social and academic integration take the negative path (Kember, 1995). Additionally, those who experience external attribution (i.e., external causes in their life such as insufficient time, work, family, friends, and unexpected events) and academic incompatibility are less likely to achieve a satisfactory final GPA for the course (Kember, 1995).

In the model, Kember (1995) includes a recycling loop between the cost/benefit variable and the student’s entry characteristics. Kember (1995) indicates that, during a student’s time in a course, his or her circumstances are likely to change; the recycling loop accommodates this reality. Students ask themselves whether the course work is worth the effort, and as long as the benefits outweigh the costs, the student will continue in the course (Kember, 1995).

Figure 3 presents the framework that incorporates components from Kember’s (1995) model and modifications based on research literature in the field. As researchers have pointed out, persistence and performance in online courses are complex and impacted by many variables and components (Munro, 1987; Kember, 1995; Rovai, 2002; Xenos, 2004).

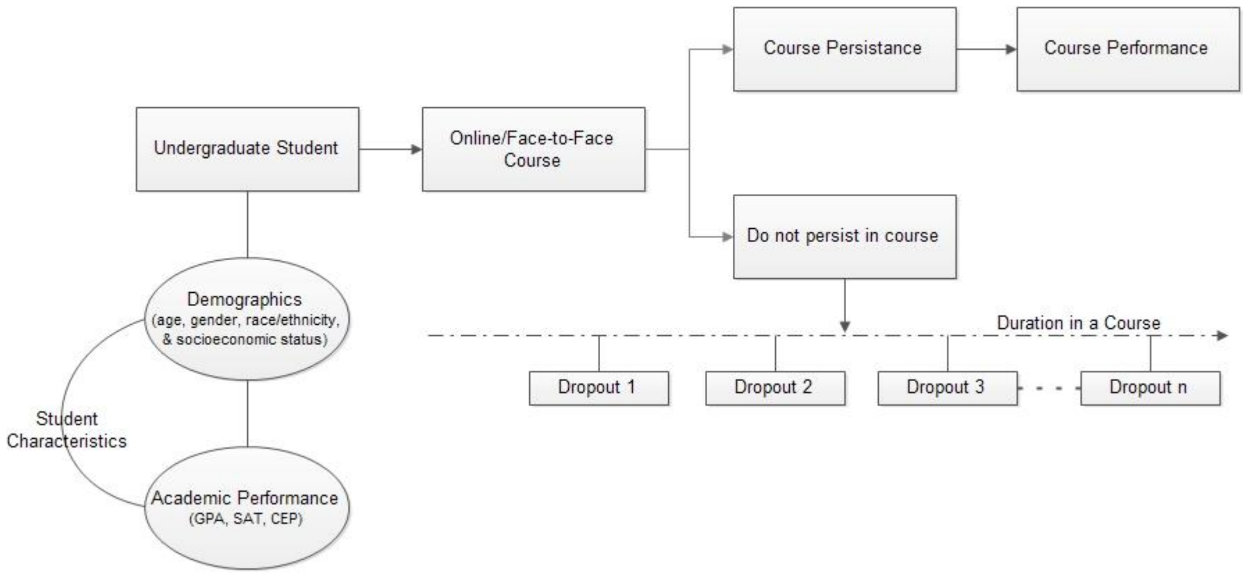

Figure 3. Kember's (1995) model modified for present study

The undergraduate student enrolling in a course, regardless of delivery format, possesses individual demographic and academic characteristics that may or may not predict that student's persistence and performance in the course. Whether the student enrolls in an online or face-to-face course, he or she may persist and complete the course. Upon completion, the student will be awarded a letter grade (course performance). If, however, the student decides to drop out (course attrition) of the course and not persist, then the student did not perform (will not receive a letter grade).

For the study at the four-year private northeastern university, many independent demographic and academic performance variables were controlled for using MLM. In Chapter 2 the researcher will outline the studies that have examined student persistence and performance in online courses and carefully examine the research to identify different contexts in the hope that clear patterns will emerge.

Relationship to Instructional Design, Development, and Evaluation

In 2002 Gustafson and Branch stated that Smith and Ragan's (1999) instructional design model had become increasingly popular with students and professionals in the field of instructional technology. There are three phases in Smith and Ragan's model: analysis, strategy, and evaluation. These three phases provide the conceptual framework for the eight steps that comprise their instructional design process (Smith & Ragan, 1999). Their eight steps are as follows:

1. analyze learning environment,
2. analyze learners,
3. analyze learning task,
4. write test items,
5. determine instructional strategies,
6. produce instruction,
7. conduct formative evaluation, and
8. revise instruction.

Learner characteristics are an important aspect of instructional design, as noted by Smith and Regan (2005) in step two above. The intent of the present study was to identify the student characteristics (or learner characteristics) that predict student success (persistence and performance) in both online and face-to-face courses.

It is "critical that (instructional) designers consider their target audiences, as this knowledge will be important in designing instruction that is effective and interesting to learners" (Smith & Ragan, 2005, p. 58). Smith and Ragan also suggest that analyzing learners who are remote can be a challenging task and that designers must dedicate substantial time to this task to develop an adequate profile.

By understanding which student characteristics predict student persistence and performance in courses, regardless of delivery format, instructional designers will be better equipped to "elevate a mundane segment of instruction into compelling, imaginative and memorable instruction" (Smith & Ragan, 2005, p. 70). Mayes, Luebeck, Ku, Akarasriworn, and Korkmaz (2011) discuss the challenge of providing high-quality online instruction, and they review the literature regarding six themes in online instruction. One such theme is how learner and instructor characteristics influence online learning. They state, "Learner characteristics can be intensified in an online environment, creating unexpected obstacles to teaching and learning" (Mayes et al., 2011, p. 152).

The identified student characteristics in combination with the desired instructional intent determine what information and instructional techniques (strategies) to use in the instruction. Smith and Ragan (2005, pp. 70–71) provide a list of many instructional strategy factors that are directly related to learner characteristics, including, but not limited to, pace of content presentation, amount of structure and organization, grouping of students, size of instructional chunks, amount of time allowed for instruction, and amount and type of learning guidance, cures, and prompts provided.

When instructional designers conduct a learner analysis and begin to write the description of the learners, it is important that the instructional designers include implications that learner characteristics have for the design of the instruction (Tongsing-Meyer, 2013). "Learner characteristics can influence instruction at the most fundamental levels" (Smith & Ragan, 2005, p. 71). Wickersham, Espinoza, and Davis (2007) also discuss the importance of designing courses to provide meaningful experience based on the learning styles of students, combined with unique approaches to teaching online.

By understanding the student characteristics that predict student persistence and performance in online courses and the face-to-face equivalents, instructional designers can adjust the instruction to accommodate the learner characteristics in either mode of instruction (online or face-to-face).

Significance of the Study

There is no single way to account for student persistence in online courses (Rovai, 2004). Persistence is a complex issue and it is not creditable to attribute persistence to any single student characteristic (Rovai, 2004; Hart, 2012). It was important to conduct this study because course attrition rates in online courses are significantly higher than for traditional, face-to-face courses (Dunagan, 2005; Holder, 2007; Street, 2010). This study did not investigate why students drop out, but it did examine which student characteristics may predict persistence and performance in online courses and the face-to-face equivalents. In other words, it answered the question, Can student persistence and performance be predicted based on student characteristics? If so, what characteristics are most important in predicting persistence and performance?

Summary

For more than a decade, online enrollments have been increasing exponentially, prompting a keen interest among educational researchers in student persistence and performance in online courses. Despite a wealth of evidence indicating that course attrition is higher in online courses than in the face-to-face equivalents, there have been only a handful of studies that attempted to understand this phenomenon through quantitative validation.

This study attempted to fill that gap. The researcher, using a multi-level linear model, examined a rich data set spanning a decade at a single institution. In Chapter 2 a case is made for the inclusion and operationalization of the variables outlined in the presented model. The case is extended and further developed in Chapter 2 by summarizing the relevant literature, revising each argument, and presenting a research design suited for identifying which student characteristics predict student persistence and performance. Chapter 3 describes the methodological and design choices made to minimize the inherent limitations of the study. In Chapter 4, descriptive data and the results are presented with a discussion of the findings that follow in Chapter 5. The conclusion identifies strengths and weakness of the research and suggests ideas for future research.

CHAPTER 2: LITERATURE REVIEW

Introduction

In 2009 President Obama announced the Access and Completion Incentive Fund, dedicating $2.5 billion to be spent over a five-year period on access and retention, intended to help the United States become the leader in college graduates worldwide (Dervarics, 2009). Each year, American College Testing (ACT) conducts the ACT Institutional Data Questionnaire, an annual survey distributed to two-year and four-year postsecondary institutions (ACT, 2012). In 2012 ACT reported that 55% of students enrolled at a four-year private institution (n=214) persist to bachelor degree completion within five years (ACT, 2012). Retention rates for first-year students who consecutively returned for the second year was reported as 67% for four-year private institutions (n = 353) for bachelor degrees (ACT, 2012). Retention rates for first-year students who consecutively returned for the second year was reported as 70% (n = 505) for students pursuing a master's level degree and 80% (n = 274) for the doctorate level (ACT, 2012).

Course attrition, as opposed to institutional persistence discussed above, is also of growing concern in higher education, and many researchers and practitioners are concerned about student persistence and performance specifically in online courses. Online course offerings are growing at an exponential rate in higher education (Allen & Seaman, 2011) and the literature has noted course attrition rates are higher for online courses than for traditional, face-to-face courses (Carr, 2000; Diaz & Bontenbal, 2001; Dunagan, 2005; Frankola, 2001; Holder, 2007; Lynch 2001; Moody, 2004; Street, 2010; Terry 2001).

This study attempted to identify the student characteristics that predict student persistence and performance in online courses and the face-to-face course equivalents. Many independent variables such as demographics and academic performance will be controlled for at a four-year private northeastern university using multilevel modeling (MLM).

History of Online Education

From correspondence courses to online courses, distance education has been part of higher education in the United States for more than 120 years. The following section is based on an infographic titled "The Evolution of Learning in Higher Education," which was created by Post University and published in 2012 by the EdTech Times:

> In 1892 the University of Chicago created the first college-level distance-learning program where students exchanged assignments and lessons through the postal service. In 1921 colleges such as the University of Salt Lake City and the University of Wisconsin began delivering education through live radio shows. Between 1918 and 1946 the Federal Communications Commission (FCC) granted licenses to some 200 colleges to deliver education via the radio.
>
> Expanding in 1963, the FCC created the Instructional Television Fixed Service (ITFS), which was a low-cost, subscriber-based-system that broadcasted content from educational institutions through the television. The University of Wisconsin created the Articulated Instructional Media (AIM) Project in 1964, which was the first attempt to identify, categorize, and systemize online learning practices. Additionally, AIM provided guidance on how to create and incorporate multimedia materials into online learning. In 1970 virtual campuses were born. Coastline Community College became the first college without a physical campus by fully televising college courses.
>
> In 1980 Learn/Alaska was created, becoming the first state educational satellite system, with students in 100 villages watching six hours of instructional television daily. By 1982 the National Technological University offered online degree courses using satellite transmission, and by 1991 the advent of the Internet changed everything. Jones International University became the first fully online university accredited by the Higher Learning Commission in 1993; it offered five online bachelor's degree programs and 24 online master's degree programs.
>
> The Asynchronous Learning Network (ALN) Web was established in 1996 by John Bourne and was touted for having the ability to deliver education anytime, anywhere through the Internet. The ALN Web eventually became the Sloan Consortium in 2008, an organization focused on improving the quality and integration of online education into mainstream higher education. In 2002 the Massachusetts Institute of Technology (MIT) launched its OpenCourseWare proof-of-concept site, which published, for free, MIT course materials, including lecture notes, exams, and videos. Its launch marked the "historic moment when an elite higher education institution shares materials from its curriculum freely and openly on the web" (EdTech Times, 2012). By 2005 online education had become mainstream.

> In 2011 Stanford University professor Sebastian Thrun launched a Massive Open Online Course (MOOC) with more than 160,000 students, and this led to a "renewed interest in the power of online education" (EdTech Times, 2012).

By 2013, though online enrollments were growing (Allen & Seaman, 2013), the value of online education was still the subject of debate among researchers.

TRANSITION TO ONLINE EDUCATION. The transition from traditional face-to-face classroom education to online education has not been without strong reactions from researchers. Critics note that faculty must expend more time and effort to teach online than face-to-face. This was the case for Visser (2000), who conducted a study comparing his own experience as an instructor of a new online course with his prior experience teaching in a traditional face-to-face course. Visser (2000) did suggest, however, that the amount of development and delivery time and effort may depend on the experience level of the instructor and the level of institutional support.

DiBiase's (2000) yearlong study of his own online course as compared to his face-to-face course contradicts Visser's work. According to DiBiase, the total teaching and maintenance time spent per learner in his online course was less than that spent in his regular face-to-face course. In contrast, a survey of chief academic officers (n = 2,800) by Allen and Seaman (2013) found that the percentage of academic leaders that believe it takes faculty more time and effort to teach online increased from 41.4% in 2006 to 44.6% in 2013. Private for-profit institutions are the lone group whose level of agreement regarding faculty effort dropped from 31.6% in 2006 to 24.2% in 2012 (Allen & Seaman, 2013).

Another concern is whether learning outcomes in online courses are comparable to those of the face-to-face courses equivalents. In annual surveys since 2003, Allen and Seaman have asked chief academic officers to rate the learning outcomes for online courses. In 2003 57.2% of academic leaders rated the learning outcomes of online courses as the same or superior to those of face-to-face course equivalents. By 2013 that number was 77% (Allen & Seaman, 2013). However, a minority (23%) of academic leaders continued to believe that learning outcomes for online courses are inferior to those of face-to-face course equivalents (Allen & Seaman, 2013). Shea, Pickett, and Li (2005) conducted a survey of 913 faculty teaching online and found that 32.6% of them perceived that online students performed better than traditional face-to-face students, with 8.8% of faculty indicating that traditional face-to-face students performed better. Interestingly, 37.6% of faculty indicated that there was no performance difference between the two groups of students (Shea, Pickett, & Li, 2005).

Additionally, critiques of online courses indicate that faculty will not readily adopt online instruction. Allen and Seaman (2013) report that only 30.2% of chief academic officers believe their faculty will accept the value and legitimacy of online course instruction. This rate is lower than the rate recorded in 2004 (Allen & Seaman, 2013). Reasons faculty would not readily adopt this mode of course delivery include (a) no monetary incentive for teaching online, (b) time spent developing an online course did not count towards promotion and tenure, (c) the perceived increase in workload when developing and delivering an online course, and (d) lack of institutional training for faculty to develop and deliver an online course (Bower, 2001). Other commonly cited barriers to adoption of this mode of course delivery are (a) course content ownership issues, (b) technical difficulties, and (c) inadequate support for both students and faculty in the new environment (Shea, Pickett, & Li, 2005).

The controversy over online courses involves concerns about whether students will have the requisite discipline and motivation, the higher course attrition rates for online courses, and whether future employers will hire someone with an online degree (Allen & Seaman, 2013).

Some faculty fear that online learning will obviate the need for instructors. It does not seem, however, that institutions have had a dip in enrollment numbers in traditional face-to-face course offerings, despite providing online course offerings (Allen & Seaman, 2007). Online enrollments continue to grow, and the field is looking for ways to capitalize on this growth.

TRADITIONAL ONLINE COURSES. The spread of computer-network communications in the 1980s and 1990s allowed teachers and students to communicate in real-time via computers, even when they were separated by distance. As the technology became more sophisticated and readily available, students and instructors could also interact asynchronously, that is, not at the same time.

Today online courses are conducted remotely via computer systems—usually the Internet. This study focused on online courses offered through a learning management system using asynchronous technologies at a private northeastern four-year university. For this study, the term *online course*, is a course taught asynchronously, with students and instructors physically separated, and delivered/accessed online, primarily without scheduled class sessions or real-time interaction (Ball State University, 2014).

TRADITIONAL FACE-TO-FACE COURSES. A *face-to-face* course as a course taught synchronously, with students and instructors physically present together, in a physical campus location (Ball State University, 2014). The instructor delivers course content during a predetermined course meeting time, typically in a brick and mortar location.

FACE-TO-FACE VERSUS ONLINE. The literature reveals a strong interest in comparing online courses to the face-to-face course equivalents, and many research studies have done this (Dillon, Dworkin, Gengler, & Olson, 2008; Boston, Ice & Gibson, 2011; Flowers, White, & Raynor, 2012; Gannon-Cook & Sutton, 2012; Cochran, Campbell, Baker, & Leeds, 2013). In 2010 the United States Department of Education released a study reporting the results of a meta-analysis of more than 1,000 empirical studies that compared online and face-to-face courses (Means, Toyama, Murphy, Bakia, & Jones, 2010). More recently, the *Chronicle of Higher Education* posted a commentary (Carlson, 2013) about a Gallup survey in which 1,000 adults were asked their opinion about the merits of online courses versus face-to-face courses (Gallup, 2013).

These recent publications have been cited numerous times, despite Clark's (1983; 1994) argument that media never influence learning. Clark (1983) declares that instructional methods determine how effective a piece of instruction is and that media's *only* influence is on cost and distribution. His argument (Clark, 1983) is that "media are mere vehicles that deliver instruction but do not influence student achievement any more than the truck that delivers our groceries causes changes in our nutrition" (p. 445).

Challenging Clark's position is Kozma (1991; 1994), who contends that the unique attributes of certain media can affect both learning and motivation (Kozma, 1991; 1994). Kozma's (1994) argument is that, "if there is no relationship between media and learning it may be because we have not yet made one" (p. 7).

Hastings and Tracey (2004) argue that technological advances have added substance to Kozma's position; most notably, the computer has changed dramatically since 1983. The authors (Hastings & Tracey, 2004) note that in 1983, (a) computers could not physically connect to the same mainframe or server, (b) they were not portable or easily programmable, (c) the Internet and World Wide Web were unknown, and (d) virtual classrooms did not exist. They seek to reframe the original debate to ask, "not *if*, but *how* media affects learning" (Hastings & Tracey, 2004, p. 30).

If one were to accept the reframed debate that Hastings and Tracey present, then it would be appropriate to examine student persistence and performance in online courses and the face-to-face course equivalents while controlling for many available independent variables. Although this is not a comparison study of persistence and performance in online versus face-to-face instruction, the data about persistence and performance in each format (online and face-to-face) are important in teasing out student characteristics that are predictive in each format individually. In the end, patterns that emerge from these data may be important to designing instruction in one, the other, or both formats.

Relevance to Theory and Practice

Albert Einstein once said, “It is the theory which decides what we can observe.” Many proponents have argued that theory allows, even forces, us to see the “big picture” and makes it possible for us to view our practice and our research from a broader perspective than that envisioned from the murky trenches of our practice (Anderson, 2004). Studying the student characteristics that predict student persistence and performance using formal models, detailed and rich data, and robust statistical methods will help higher education administrators and faculty put into practice more effective online courses in the best interest of students, parents, institutions, and society.

Online course delivery allows for flexibility of access from anywhere and usually at any time—essentially, it allows participants to collapse time and space (Cole, 2000). Considering these advantages, it is not surprising that institutions are adopting online course delivery, as indicated by the rapid growth of online enrollments (Allen & Seaman, 2011). This tremendous increase in online enrollment in the last 10 years, combined with the need for research on the student characteristics that can predict student persistence and performance in online courses, make the relevance of this study apparent.

The results of this study can be used to inform instructional designers and educators of facts about their students that may influence their course design choices. These data, with additional validation, may also be important to those in institutions who set or monitor online instruction measures and quality standards. Such measures and standards may also be informed by the characteristics that help predict higher student persistence and better student performance.

Factors Influencing Student Persistence and Performance

Studies conducted on variables that influence student persistence and performance in online courses have yielded mixed findings (Finnegan, 2005; Aragon & Johnson, 2008; Harrell & Bower, 2011). There is, however, a consensus in the literature that course attrition, especially in online instruction, is a complex phenomenon. Munro (1987) describes dropout (course attrition) as similar to an automobile accident in that it has a single symptom with many possible causes. And yet Xenos (2004) notes that “it is important for administrators to be able to identify the dropout [course attrition] causes” (p. 348). Regarding this daunting task, Rovai (2002) states, “There is no simple formula that ensures student persistence. Adult persistence in an online program (courses) is a complicated response to multiple issues. It is not credible to attribute student attrition (course) to any single student, course, or school characteristic. There are numerous internal and external factors that come into play, as well as interactions between factors” (pp. 12–13). This study helps to identify the characteristics of undergraduate students that predict student persistence and performance in online courses and the face-to-face equivalents. The themes and data results identified in this study will help instructional designers, educators, and administrators as they design online courses, refine online instruction, and monitor quality standards.

Table 1 presents a detailed summary of the studies that examined factors associated with the ability of students to persist and perform in online courses. After Table 1 is a synthesis of the results of the literature highlighted in the summary table and how the findings relate to the current study.

Table 1. Summary of Literature

Author, Year	Title	Research Question/Purpose	Method	Findings	Limitations	How My Study Will Build Upon the Literature
Sullivan, 2001	Gender differences and the online classroom: Male and female college students evaluate their experiences	Is there anything about the online classroom that has made it easier for you to learn, achieve academic goals, or participate in class discussions? Is there anything that made it harder?	Survey Instrument	Positive comments outnumbered negative ones by a 2 to 1 ratio. 25 out 38 males had something positive to say about the online learning environment, while 116 out of 157 females had something positive to say. Negative comments were about specific teaching strategies and conduct, specific course design issues (not enough feedback, confusing directions), and problems related to hardware and software.	Data collection was done through a survey that relies on self-reported data.	It will examine all student-characteristic variables through data collected by the institution that is not dependent on self-reporting.
Kemp, 2002	Persistence of adult learners in distance education	The purpose of this study was to investigate the relationship between persistence, life events, external commitments, and resiliency in undergraduate distance education.	Stepwise Discriminant Analysis & ANOVA	The best predictors of persistence in this study were attachment, persistence, work commitments, valuing, resilience, initiative, recruiting, general resilience, insight. Students with high levels on 9 measures of resilience were more likely to succeed in their undergrad studies.	Results not generalizable and were focused on first-time undergraduate distance students at a single institution.	It will examine all undergraduate students.

Author, Year	Title	Research Question/Purpose	Method	Findings	Limitations	How My Study Will Build Upon the Literature
Muse, 2003	The web-based community college student: An examination of factors that lead to success and risk	1. Which of these factors—computer confidence, enrollment encouragement, need for support, preparation, computer skills, tenacity, study habits, web skills, motivation, study environment, background confidence, and external locus of control—will be used to compute a student's ability to successfully complete a web-based course? 2. Will a weighted combination of the critical factors (identified by a survey) indicate which students are at risk of failing to successfully complete the web-based class? 3. Will age, gender, GPA, number of hours currently worked, years since last college course, number of previous distance learning courses taken, education level, and number of credits in the current semester significantly affect successful completion of web-based classes? 4. What reasons are reported most often for student dropout (course attrition) in web-based classes?	Mixed Methods	The corresponding answers follow: 1. Computer skills, study environment, external locus of control, computer confidence, Web skills, motivation, and background preparation were useful in discriminating between successful and unsuccessful web-based community college students; 2 The significant critical factors were GPA, study environment, age group, time since last college course, and background prep.; 3. GPA, age, and years since last college course provided a basis for discriminating between successful and unsuccessful students; the other factors did not. Gender was not computed (nor was it dropped in the discriminant function analysis) in the original study. This researcher computed the correlation of gender and the criterion variable separately using a bivariate approach. When using Fisher's Exact Test, gender was insignificant as a discriminating variable. Answer to question 4: Varied as the data was qualitative.	Results not generalizable.	It will utilize MLM and data collected by the institution that are not dependent on self-reporting.
Parker, 2003	Identifying predictors of academic persistence in distance education	Locus of control, as measured by Rotter's locus of control scale, is a significant predictor of academic persistence. Locus of control scores increase, move toward internality, over the course of a semester for students enrolled in a web-based instruction class.	Survey Instrument	Locus of control and academic persistence were shown to have a correlation of .83 ($p = .05$). Students with internal locus of control, self-motivated, were more likely to complete the online course than students who scored as externally motivated. Students who enroll in online courses tend to become more self-motivated than students who attend traditional courses. Change in locus of control scores by the students enrolled in the traditional sections of the courses was not significant.	Data collection was done through a survey that relies on self-reported data.	Study conducted at a four-year private northeastern university.

Author, Year	Title	Research Question/Purpose	Method	Findings	Limitations	How My Study Will Build Upon the Literature
Dupin-Bryant, 2004	Pre-entry variables related to retention [course attrition] in online distance education	Identify pre-entry variables related to course completion by developing a predictive model of student retention (course attrition) in online distance education courses. Are there pre-entry variables that distinguish individuals who complete university online distance education courses from those who do not?	Discriminant Analysis	Prior educational experience such as cumulative grade point average, class rank, and number of previous courses completed online related to persistence in online courses.	Did not examine demographic data.	It will examine many available independent variables, including demographic data.
Morris, Finnegan, & Wu, 2005	Tracking student behavior, persistence and achievement in online courses	What is the relationship of student participation to student persistence and achievement online? What are the differences and similarities between completers and withdrawers in various measures of student behavior online?	Multiple Linear Regression & Observation	Completers engaged in online learning activities with greater frequency and spent more time than unsuccessful, withdrawing students. There was a statistically significant difference in the behaviors of completers and withdrawers.	Results not generalizable.	It will utilize MLM to nest data within contextual/aggregate unit.
Morris, Wu, & Finnegan, 2005	Predicting retention [course attrition] in online general education courses	How accurately can a student's persistence be predicted in online learning? Which predictors are the most important with respect to predictive accuracy of a student's group membership (completion and withdrawal)? Can a prediction/classification rule be developed that may be used with a "new" analysis unit (e.g., students)?	Predictive Discriminant Analysis & MANOVA	High school GPA and mathematic ability were found to be the most important predictors in subset A. Locus of control and financial assistance were found to predict students' group membership with 74.5% accuracy for subset B.	Results not generalizable.	It will examine all undergraduate students.
Nash, 2005	Course completion rates among distance learners: Identifying possible methods to improve retention [course attrition]	The purpose of this study was to determine why students dropped or failed a distance learning course and to identify methods that might improve success and increase retention (course attrition).	Survey Instrument	Students who dropped out of distance learning courses expected them to be easier than the face-to-face course equivalent.	Data collection was done through a survey that relies on self-reported data.	It will use data collected by the institution that is not dependent on self-reporting.

Author, Year	Title	Research Question/Purpose	Method	Findings	Limitations	How My Study Will Build Upon the Literature
Holder, 2007	An investigation of hope, academics, environment and motivation as predictors of persistence in higher education online programs	To what extent do measures of students' hope, as well as academics, motivation and environment predict persistence in online learning?	Regression, ANOVA, & Survey Instrument	Three major criteria differentiating retention (course attrition) in the sample. Successful students prone to persist tended to score higher in emotional support, self-efficacy, and time and study management	Data collection was done through a survey that relies on self-reported data.	It will use data collected by the institution that is not dependent on self-reporting.
Levy, 2007	Comparing dropouts [students who do not persist] and persistence [students who do persist] in e-learning courses	The aim of this study was to look at the two main constructs proposed by literature (academic locus of control and students' satisfaction) and their impact on students who drop out (do not persist) from e-learning courses.	Survey Instrument	Student satisfaction from e-learning is a major factor in students' decision to complete or drop from an online course. Academic locus of control was not found to play a major role in predicting dropout (course attrition), and the majority of the demographic characteristics were not found to be significantly different between completers and noncompleters. However, college status and graduating term were.	Data collection was done through a survey that relies on self-reported data and examines only course persistence.	It will examine both student persistence and performance.
Aragon & Johnson, 2008	Factors influencing completion and noncompletion of community college online courses	Is there a significant difference in demographic characteristics, enrollment (hours enrolled) characteristics, academic readiness, and self-directed learning readiness between students who complete and do not complete online courses? What are the self-reported reasons for student noncompletion of online courses?	Regression, ANOVA, & Survey Instrument	There was no significant difference between completers and noncompleters with regard to age, ethnicity, financial aid eligibility, and placement in developmental education courses. Completers enrolled in more online courses and had a higher GPA than noncompleters. No significant difference was found between completers and noncompleters in their self-directed learning scores.	Results not generalizable and based on one semester of student data.	It will examine data over the span of 11 years within one institution.
Müller, 2008	Persistence of women in online degree-completion programs	Why do women persist in online courses? Why do they fail to persist or stop out? How do factors affect women learners' persistence?	Qualitative Study	Findings suggest that the variable support plays a greater role in those students who persist.	Results not generalizable and sample size was 20.	It will utilize MLM to nest data within contextual/aggregate unit.

Author, Year	Title	Research Question/Purpose	Method	Findings	Limitations	How My Study Will Build Upon the Literature
Liu, Gomez, & Yen, 2009	Community college online course retention [persistence] and final grade: Predictability of social presence	Can social presence predict course retention (persistence) in a community college? Can social presence predict online course final grade in a community college?	Binary & Ordinal Logistic Regression Analysis & Survey Instrument	The results suggest social presence is a significant predictor of course retention (persistence) and final grade in the community college online environment.	Data collection was done through a survey that relies on self-reported data.	It will use MLM to nest data within contextual/aggregate unit.
Park & Choi, 2009	Factors influencing adult learners' decision to drop out or persist in online learning	Do the dropouts (students who do not persist) and persistent learners (students who do persist) of online courses show differences in their individual characteristics, external factors, and internal factors? What factors are significant in predicting learners' decisions to drop out of online courses?	MANOVA & Survey Instrument	Learners' age, gender, and educational level did not have a significant and direct effect on the (student's decision to not persist) dropout decision. Although the result does not claim that individual characteristics should be ignored, it can be concluded that individual characteristics have little influence on the decision to drop out and thus can be considered as trivial.	Data collection was done through a survey that relies on self-reported data.	It will examine all student characteristic variables through data, collected by the institution, that is not dependent on self-reporting.
Ojokheta, 2010	A path-analytic study of some correlates predicting persistence and student's success in distance education in Nigeria	1. What predictors enhance persistence and student success? 2. To what extent do the predictors, taken collectively, enhance distance learners' effective learning?	Path Analysis	The learner's learning environment and the provision of support services to the learning contributed significantly to predicting persistence of students in online courses.	Data collection was done through a survey that relies on self-reported data.	It will use data, collected by the institution, that is not dependent on self-reporting.
Harrell & Bower, 2011	Student characteristics that predict persistence in community college online courses	Which student characteristics can be used to best predict the persistence of community college students in online courses?	Stepwise Logistic Regression	A three-variable model (auditory learning style, GPA, and basic computer skills) was significant in predicting whether or not a community college student would persist in an online course.	Data collection was done through a survey that relies on self-reported data.	It will use data, collected by the institution, that is not dependent on self-reporting.

The oldest study included in this literature review was conducted by Sullivan (2001), and it examined gender and why students persisted in online courses. He found that, regardless of gender, students' perceptions of the quality of online teaching were largely positive: positive comments outnumbered negative ones by a two to one ratio (Sullivan, 2001). Both genders did make a substantial number of negative comments, including specific comments about teaching strategies and conduct, specific course design issues (not enough feedback, confusing directions), and problems related to hardware and software (Sullivan, 2001). Overall, his results imply that it is possible to create an online course that both men and women will respond favorably to and that will benefit a wide variety of students. Further, the data clearly suggest that online courses could benefit nontraditional female students more, and that the more options and flexibility are provided, the more successful the nontraditional female student will be.

The current study examined not self-reported data, but existing data related to the characteristics of students. One such characteristic is gender because Sullivan's (2001) work reveals that more female students enroll in online courses and that they are more likely to persist and perform in online courses.

The purpose of Kemp's (2002) study was to investigate the relationships between persistence, life events, external commitments, and resiliency in undergraduate online courses (Kemp, 2002). Using student scores from the resiliency attitudes scale (RAS), the life events inventory, and one questionnaire relating to external commitments, Kemp (2002) was able to utilize stepwise discriminant analysis and ANOVA to analyze the data.

Her results show that (a) having participated previously in an online course (completed or not); (b) external commitments such as family, home, and community commitments; and (c) life events were not predictors of persistence in an online course. However, she did find that work commitment was a significant predictor of student persistence.

Her study focused on first-time undergraduate online students at a single institution, and therefore the results are not generalizable. Additionally, she did not examine demographic variables or academic performance, but relied on self-reported data. In contrast to Kemp's work, this study examined undergraduate demographic and academic performance variables (student characteristics); it did not rely on self-reported data but rather on an existing rich data set (n = 42,280) spanning from fall 2002 to spring 2013. This study examined undergraduate online students at a single, four-year private northeastern institution and therefore the results are not generalizable. Kemp's study was included here because it is one of the few quantitative studies examining student persistence in online courses. While the methodology used in Kemp's study was not employed in the current study, it does contribute to the field.

Muse (2003) examined factors such as computer confidence, enrollment encouragement, need for support, preparation, computer skills, tenacity, study habits, web skills, motivation, study environment, background confidence, and external locus of control to identify which factors could be used to compute a student's ability to successfully complete (persist) a web-based (online) class. He also included demographic variables and investigated the reasons that are most often reported by students who drop out of web-based classes. Additionally, he defined a failing student (a student who persisted but did not perform) as one receiving a grade of F in the online course. Muse utilized multiple linear regressions and discriminant function analysis as well as a set of interview questions. Results indicate that computer skills, study environment, external locus of control, computer confidence, web skills, motivation, and background preparation would be useful in discriminating between successful and unsuccessful students.

Additionally, critical factors that indicated which students were at risk for failing to successfully (persist) complete the web-based (online) class included grade point average (GPA), study environment, age group, time since last college course, and background prep (Muse, 2003).

Age, GPA, and number of years since last college course were statistically significant, and these variables affected the differentiation of students into successful (students who persisted) and nonsuccessful (students who did not persist) groups; the others did not (Muse, 2003). Gender was not computed (nor was it dropped in the discriminant function analysis) in the original study (Muse, 2003). This researcher computed the correlation of gender and the criterion variable separately, using a bivariate approach (Muse, 2003). Using Fisher's Exact Test, gender was insignificant as a differentiating variable (Muse, 2003). In contrast to Muse's (2003) study, this study utilized MLM methodology and data that existed at the institution that was not self-reported. These decisions contributed to the study's reliability. Additionally, because of the conflicting results of the gender variable, gender was examined in this study.

At a community college in Arizona, Parker (2003) investigated whether locus of control, as measured by Rotter's Locus of Control scale, was a significant predictor of persistence for students enrolled in online courses. Employing chi-square, she found that locus of control was a significant predictor of course persistence and that students who enrolled in an online course tended to become more self-motivated than students who enrolled in face-to-face courses.

As with many of the studies included in this literature review, Parker relied on self-reported data. However, she strengthened her study by employing an experimental design using a single group in pretest-posttest design where class participants were given the survey instrument in the first week of class and then again in the last week of class. She was then able to conduct a correlation analysis to determine the relationship between locus of control and persistence.

For the current study, both online courses and the face-to-face equivalents were examined, and the study relied on all available independent variables under the categories of demographics and academic performance. The MLM design allowed for examination of the existing data set grouped by more than one level, as previously described in Chapter 1. The methodology allowed for the identification of the student characteristics that might predict student persistence and performance in online courses and the face-to-face equivalents.

In 2004 Dupin-Bryant identified pre-entry variables related to course completion (persistence) and noncompletion (did not persist) in university online courses. She identified pre-entry variables that distinguished between students who had completed online courses and those students who had not. Noncompleting students tended to be lower-division students whose cumulative grade point averages were lower than those of completing students. Prior educational experience, including cumulative grade point average (GPA), class rank (freshman, sophomore, junior, senior), and number of previous courses completed online were found to predict student persistence in online courses in her study. Of all the pre-entry variables she used in the study, only one, years of computer experience, did not make an important contribution to student persistence.

Like Dupin-Bryant's study, the current study examined pre-entry characteristics, including prior educational experience, such as grade point average, participation in a concurrent enrollment program as well as scholastic aptitude test (SAT) scores. Additionally, the study controlled for many available independent variables.

Morris, Wu, and Finnegan (2005) examined student engagement in 13 sections of three undergraduate general-education asynchronous online courses. The authors wanted to examine (a) the relationship of student course participation to student course persistence and achievement in online courses, (b) the differences and similarities between completers (students who persisted) and (c) withdrawers (students who did not persist), using various measures of student behavior online, and they also examined how accurately measures of student participation predicted achievement in online courses. The data were analyzed using multiple linear regression techniques (Morris, Wu, & Finnegan, 2005). Additionally, the authors defined successful completers (performance) as undergraduate students who completed the online course, receiving a grade of A, B or C.

The authors found that high school grade point averages and math SAT scores were the most important predictors in online course completion. With regard to performance, students who exhibited a higher grade point average prior to enrollment in the online course were more likely to perform (Morris, Wu, & Finnegan, 2005).

The institution of study's definition for performance, which was used by Morris, Wu, and Finnegan, was also used for the current research study (Ball State University, 2014). This study also examined SAT scores and GPA prior to enrollment at the institution to examine student persistence and performance.

Through the use of a survey instrument, Nash (2005) studied why community college students dropped (did not persist) or failed (did not perform) an online course and identified methods that might improve success (persistence and performance) and increase retention (course attrition) in online courses. He found that precourse orientations and supplemental tutoring services are necessary to improve online course completion rates. Students in the study identified time constraints, the impression that online courses were easier than face-to-face courses, and test taking skills as reasons why they dropped an online course.

The present study examined what student characteristics predicted persistence and performance in online courses and the face-to-face equivalents. The findings of the current study may inform administrators' decisions or faculty course design decisions with regard to specific remedies to improve the persistence of students in online courses.

Holder (2007) developed a 60-item online survey, based on previous research in persistence, to examine online course persistence in a variety of online bachelor- and master-level courses. The survey was distributed to participants and the data were analyzed using logistical regression. The results suggested that a three-variable model (auditory learning style, GPA, and basic computer skills) was significant in predicting whether community college students would persist in an online course.

While Holder's study is of interest because he examined a variety of online courses, he utilized a survey that allowed participants to provide data through self-reporting. Data were collected from both undergraduate and graduate students, but students were not grouped in these categories (undergraduate and graduate); rather the findings were merged into one large online group. The demographic variables included gender, age, race/ethnicity/academic pursuit (associate, bachelor's, master's), employment status, and previous online experience. Missing from his demographic variables was financial aid status, an independent variable that was included in the current study.

Levy (2007) examined two main constructs, academic locus of control and students' satisfaction with online courses, and their impact on students' dropping out (not persisting) of online courses. The results show that students' satisfaction in online courses is a major factor in their decision to complete or drop an online course. Academic locus of control was not found to play a major role in predicting student dropout from online courses. Additionally, the majority of the demographic characteristics (gender, age group, residency status, academic major, GPA, and weekly working hours) were not found to be significantly different between those students who persisted and those who dropped out of online courses (Levy, 2007). The current study examined online courses and the face-to-face equivalents, unlike Levy's study, which examined only online courses.

Additionally, Levy indicates that studies related to course attrition have not provided a clear profile of those students who do not persist. He characterizes those students who do not persist as "students that voluntarily withdraw from online courses while acquiring financial penalties" (p. 188). For this study, students who do not persist are characterized as students who enroll in an online course but drop the course prior to the course end date.

The study conducted by Aragon and Johnson (2008) compared students who persisted with those that did not persist in online courses based on demographic characteristics, enrollment (credit hours enrolled) characteristics, academic readiness, and self-directed learning readiness. The authors found that there was no significant difference between persisters and those students who did not persist with regard to age, ethnicity, financial aid eligibility, and placement in developmental education courses. Persisters enrolled in more online courses and had a higher GPA than those students who did not persist, and no significant difference was found between persisters and those who did not persist in their self-directed learning scores (Aragon & Johnson, 2008).

Additionally, the authors defined course completion (performance) as a grade of A, B, C, or D. Course noncompletion (performance) was defined by a grade of F, Dr for drop, W for withdraw, or I for incomplete. Their study was one of the few studies to examine and define completion (performance). For the current study, performance, is defined as successful completion of an online or face-to-face course with a grade of C or better for undergraduate students (Ball State University, 2014).

Through a qualitative case study, Müller (2008) investigated the factors that influence women learners' course persistence in undergraduate and graduate online degree-completion programs at a college in the northeastern United States. From an analysis of the case study's data she identified patterns or themes that reveal the complexity of factors affecting women's course persistence, but findings suggest that the variable, support, plays a greater role for those students who persist.

Müller's study assumes that more women take online courses at this particular institution. While the institution may have a higher number of enrolled women, readers cannot deduce that women enroll in online courses more than men do. To mitigate this, the author could have simply provided the statistics for the total number of men and women enrolled in online courses at the institution. Although her sample size was small and focused on women, Müller reaffirms what has previously been stated in the literature—student persistence is a complex phenomenon and many factors contribute to student persistence and performance in online courses (Rovai, 2002; Xenos, 2004; Munro, 1987).

In another study conducted by Liu, Gomez, and Yen (2009), the authors investigated whether or not students' social presence in an online course could predict retention (course persistence) and final grade at a community college. Course retention (persistence) was defined as successfully completing a course with an A to C grade. They defined students who do not persist as Levy (2007) did—as students who dropped after the institution's census date and received financial penalties. Data collection was done through a social presence and a privacy questionnaire.

The data set utilized by the authors is based on self-reported data; they had a small response rate, and their data represented only one semester. In contrast, the current study examined data spanning from fall 2002 to spring 2013 at a single institution, for a single student spanning of his or her career at the institution. Additionally, the researcher could examine a single student and his or her participation in multiple online courses and the face-to-face equivalents if the student was enrolled in more than one course at the institution. Through the use of MLM methodology the existing data set for participants could be organized and grouped at more than one level (student, and academic school/college levels).

Park and Choi (2009) investigated whether students who persisted or did not persist differed in individual characteristics (e.g., age, gender, and education level), external factors (e.g., family and organizational supports), and internal factors (e.g., satisfaction and relevance as subdimensions of motivation). Utilizing a survey instrument based on Keller's Course Interest Survey to collect data, the authors found that students who persisted and those who did not showed statistical differences in perceptions of family and organizational support, and of satisfaction and relevance. Their study reveals that learners' age, gender, and educational level did not have a significant and direct effect on their decision to drop out out of an online course.

The current study utilized MLM design because the existing data set for participants was organized and grouped at more than one level. Park and Choi (2009) relied on self-reported data, but this study will utilize existing institutional data.

Through path analysis, Ojokheta (2010) examined predictors that enhanced student persistence and to what extent the predictors, taken collectively, enhanced online learners' learning. Through the collection of self-reported data, the author found that a learners' learning environment and the provision of support services to the learner contributed significantly to predicting persistence of students in online courses; path analysis was used to explain the causal relationship between independent and dependent variables. Just as with the majority of studies outlined in Chapter 2, Ojokheta's work relies on self-reported data, which can be untruthful or inaccurate.

Harrell and Bower (2011) examined the effects of learning style, locus of control, computer experience and access, and online course experience on course persistence of community college students in online courses. Relying on self-reported data, a logistical regression analysis identified a three-variable model (auditory learning style, grade point average, and basic computer skills) that was significant in predicting online student success (persistence). Six pre-entry variables were responsible for distinguishing between student course persisters and students who did not persist: (a) cumulative GPA, (b) class rank, (c) searching the Internet training, (d) number of previous courses completed online, (e) operating systems and file management training, and (f) Internet applications training.

The current study built on Harrell and Bower's work by including the variable cumulative GPA; and instead of discriminant analysis, the MLM methodology was utilized because the existing data set for participants was organized and grouped at more than one level.

Most of the studies outlined above relied heavily on self-reported data, which, being based on information obtained from participants, can be inaccurate. Such self-reported data is typically collected through a survey questionnaire, which the authors in most cases stated they had validated. These studies did not examine both student persistence and performance in both online course and the face-to-face equivalents. Finally, none of these studies utilized MLM methodology to allow for the nesting and grouping of data, and the data sets were limited to single semesters as opposed to spanning a decade at a single institution. Previous studies have reached no consensus on which student characteristics predict student persistence and performance in online courses and the face-to-face equivalents. Some report that student characteristic have significant influence on a student's decision to drop out of an online course (Sullivan, 2001; Kemp, 2002; Levy, 2007; and Park & Choi, 2009), while others claim that those characteristics have only a minor, indirect, or no effect (Muse, 2003; Parker, 2003; Bunn, 2004; Dupin-Bryant, 2004; Nash, 2005; Holder, 2007; and Aragon & Johnson, 2008).

PREDICTOR: INDEPENDENT VARIABLES (IV). Based on a review of the literature, control variables (under the categories of demographic and academic performance) were selected. The complete list of independent variables are in Table 2 below.

Table 2. Predictor (IV)

Demographics
Age (*type of variable)*
▪ 16-46 (undergraduate students)
Gender *(nominal, dichotomous variables)*
▪ Female
▪ Male
Race/Ethnicity *(nominal variable)*
▪ American Indian
▪ Asian Pacific Islander
▪ Black African American
▪ Hispanic
▪ Non-Hispanic Multicultural
▪ Non-Resident Alien
▪ Unknown
▪ White
Financial Aid *(nominal variable)*
▪ Applied, but no need for aid
▪ Did not use financial aid
▪ Quartile 1: 0 < 17652
▪ Quartile 2: 17652 ≤ 26174
▪ Quartile 3: 26174 ≤ 34242
▪ Quartile 4: 34242 ≤ ∞
Academic Performance
▪ Grade Point Average (GPA) Prior to Enrollment at Institution
▪ Concurrent Enrollment Programs (CEP)
▪ Scholastic Aptitude Test (SAT)
▪ ▪ Math
▪ ▪ Verbal

RATIONALE FOR INDEPENDENT VARIABLE SELECTION. A number of demographic variables have been found to play a role in student persistence and/or performance in online courses. For example, an increase in the age of online course participants corresponded to a decreased likelihood of course persistence (Mathes, 2003; Muse, 2003; Menager-Beeley, 2001). As opposed to P. B. Moore (2001) and Valasek (2001), who found that as the age of the student increases, the student's likelihood of completing the course increases. However, other authors such as Park and Choi (2009), Aragon and Johnson (2008), and Levy (2007) found that age had no impact on course attrition in online courses. A number of studies have examined the influence of gender on course attrition in online courses and—as with age—have yielded varied results. In studies conducted by Park and Choi (2009) and Levy (2007), gender was found to not be significantly different between students who persisted and those who did not persist. In contrast, three studies found that gender did influence course persistence (Aragon & Johnson, 2008; Valasek, 2001); specifically, women were found to be more persistent than men in online courses.

Ethnicity has also been examined in multiple studies (K. Moore et al., 2002; P. B. Moore, 2001; Sullivan, 2001). In the P. B. Moore (2001) and K. Moore et al. (2002) studies, minority students were found to be less persistent in their online courses than White students. K. Moore et al. (2001) discovered that student performance was impacted greatly by the lack of access to the technology needed to complete course assignments. Although these two studies found ethnicity to be a predictor of student course persistence in online courses, it was found to have no impact by Levy (2007) and Aragon and Johnson (2008).

Studies have also examined socioeconomic status (Parker, 2003; Morris, Finnegan, & Wu, 2005; Aragon & Johnson, 2008). The variable *socioeconomic status* has been defined in the literature many ways. Aragon and Johnson (2008) defined *financial aid* as whether or not the student applied for it and whether or not the student received it. Morris, Finnegan and Wu (2005) simply noted whether or not the student received financial aid in any form, and Parker (1999) identified the funding source. Yet, Harrell and Bower (2011) did not provide a definition. Additionally, results reported in the literature are varied. For example, Parker (1999) concluded that financial aid was significantly correlated with course persistence, whereas Aragon and Johnson (2008) found it was not.

For this study, socioeconomic status was defined and modeled after Srinivas's (2012) doctoral work. Srinivas (2012) states that "financial need is an indicator of a student's general socioeconomic status" (p. 24). In general terms, the cost of attending college is subtracted from the family's expected financial contribution (Srinivas, 2012). This expression is the approximate amount of financial aid needed for students in order to cover the costs of college attendance. Srinivas (2012) identifies five categories of financial need, and she rank-orders them from low to high as follows:

1. No financial aid application;
2. Filed application, but no need;
3. Low financial need;
4. Medium financial need; and
5. High financial need.

This study refines Srinivas's (2012) categories by using quartiles with need categories denoted by dollar amount. Quartiles are calculated by the dollar amount of the students' financial need based on the Free Application for Federal Student Aid (FAFSA) methodology. The categories used in this study are as follows:

1. Filed application, but no need;
2. Filed application, but did not use financial aid;

3. Quartile 1 (Q1): 0 < \$17,652;
4. Quartile 2 (Q2): \$17,652 ≤ \$26,174;
5. Quartile 3 (Q3): \$26,174 ≤ \$34,242;
6. Quartile 4 (Q4): \$34,242 ≤ ∞.

As detailed above, there is no consensus regarding the ability of demographic variables to predict student persistence and performance in online courses. This study examined each of these demographic variables to determine if any individual variable or combination of variables can help institutions better predict student persistence and performance in online courses and the face-to-face equivalents.

Variables related to academic performance have also been found to play a role in persistence and performance. This study examined academic performance variables as well. College grade point average (GPA) was a significant predictor of course persistence in studies conducted by Dupin-Bryant (2004), Morris, Finnegan, and Wu (2005) and Aragon & Johnson (2008). For this study, prior GPA was examined for undergraduate students as well as concurrent enrollment programs (CEP) credit awarded by the institution in a presentation Lowenthal (2014), indicated that GPA and SAT are not good predictors of student persistence and performance in online courses.

Conclusion

As the above summaries of 15 studies show, existing research in this field

1. relies heavily on self-reported data,
2. relies on the validation of a survey questionnaire,
3. does not examine both student persistence and performance in online courses and the face-to-face equivalents,

4. does not examine online courses and the face-to-face equivalents,
5. does not utilize MLM methodology to allow for the nesting and grouping of data, and
6. does not incorporate a large data set spanning multiple years at a single institution.

Previous studies have reached no consensus on which student characteristics predict student persistence and performance in online courses and the face-to-face equivalents. Some report that student characteristic have significant influence on a student's decision to drop out of an online course (Sullivan, 2001; Kemp, 2002; Levy, 2007 and Park & Choi, 2009), while others claim that those characteristics have only a minor, indirect, or no effect (Muse, 2003; Parker, 2003; Bunn, 2004; Dupin-Bryant, 2004; Nash, 2005; Holder, 2007; and Aragon & Johnson, 2008).

Most people are convinced that online education presents an excellent opportunity to increase higher education access for a broad spectrum of individuals who may not otherwise be able to participate or who choose not to participate in traditional face-to-face courses. Although in a recent study by Fike and Fike (2008) the authors found taking online courses to be a strong predictor of student retention within the institution, yet student persistence in online courses continues to be an issue of concern, with many higher education institutions reporting persistence rates in their online courses as much lower than those in face-to-face courses. The author of the present study hoped to contribute to the literature by identifying the student characteristics that predict student persistence and performance in online and face-to-face courses.

The results of this study can be used to inform instructional designers and educators of audience facts that may influence their course design choices. These data, with additional validation, may also be important to those in institutions who set or monitor online instruction measures and quality standards. Such measures and standards may also be informed by the characteristics that suggest higher student persistence and better student performance.

CHAPTER 3: METHODOLOGY

Study Design

This study attempted to identify the student characteristics that predict student persistence and performance in online courses and the face-to-face course equivalents. Many independent demographic and academic-performance variables were controlled for at a four-year private northeastern university, using multilevel modeling (MLM). Chapter 3 describes in detail the design of the study.

Many kinds of data have a hierarchical, nested, or clustered structure (Goldstein, 2011). Students enrolled in courses (regardless of delivery format) are *nested* within an academic school/college. When data are organized in this manner it is clear that the data are no longer independent, so any statistical model employed must follow a more general dependence structure in which observations belonging to the same group can be correlated.

Multilevel modeling (MLM) provides a more effective way to analyze data where the observations are not independent; MLM can correctly model correlated error. In the general linear model family (i.e., regression and factor analysis), “uncorrelated error is an important but often violated assumption of statistical procedures” (Garson, 2013, p. 3). When data are clustered by one or more grouping variables, as in this study, violations can occur because error terms are not independent (Garson, 2013). For instance, predicted student performance and errors in predicting performance may cluster by course modality (online or face-to-face) and/or academic major. The standard errors computed for prediction parameters will be wrong because clustering occurs due to the grouping factor (Garson, 2013). MLM can lead to conclusions that are substantially different from those of conventional regression analysis (Garson, 2013).

The MLM design was selected for this research study because the existing data set for participants was organized and grouped at more than one level, as depicted in Figure 4 below.

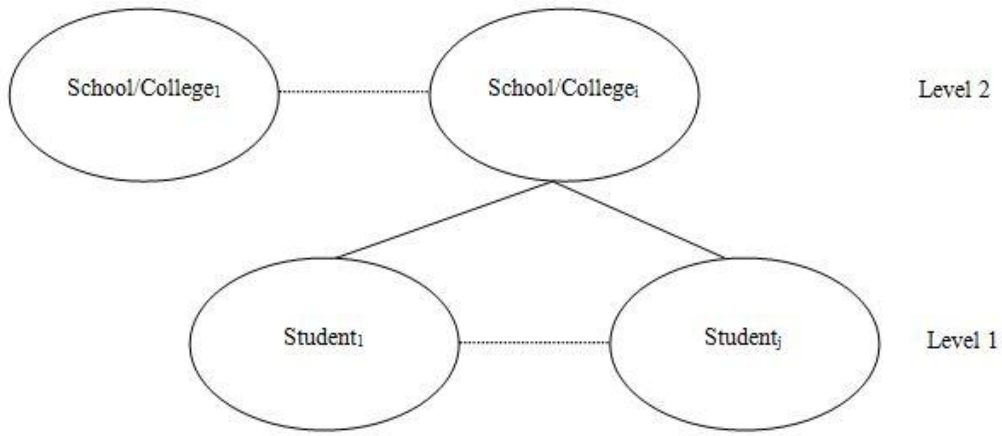

Figure 4. Multilevel Modeling Nested Levels

As previously indicated, when a student enrolls at an educational institution he or she also enrolls in an academic school/college, represented as Level 2 in the diagram above. This study includes two levels; the first-level unit is the individual student, clustered or nested in the second-level unit, which is the academic school/college. The sample includes repeat measures because some students took more than one course in more than one semester. The MLM methodology will make it possible to identify student characteristics that may predict student persistence and performance in online courses and the face-to-face equivalents.

This chapter provides a detailed explanation of the methodology employed for this study, including its advantages over other analytical techniques. The remainder of this chapter includes information on research design, independent and dependent variable selection, and data sources.

Research Questions

These are the study's research questions:

1. Which undergraduate student characteristics best predict student success (persistence and performance) in online courses?
2. Which undergraduate student characteristics best predict student success (persistence and performance) in face-to-face courses?
3. Is there a difference between the characteristics of undergraduate students who successfully complete (persist) online courses and the characteristics of those whose performance is passing (perform)?
4. Is there a difference between the characteristics of undergraduate students who successfully complete face-to-face courses (persist) and the characteristics of those whose performance is passing (perform)?

Data

SAMPLE. The university has offered online education courses for over 10 years, during which time it has been collecting data. The data set available for this research spans from fall 2002 to spring 2013. The sample for this study was 42,280 students, which accounts for 25,167 total unduplicated students. This data set was selected because it spanned a considerable number of years. The sample in this study was selected as a matter of convenience: that was the size of the total data available from fall 2002 to spring 2013. In Chapter 4 there is a discussion of how the data set was cleaned. This rich data allowed for the examination of student course persistence and performance over the entire span of the students' enrollment at the university.

Since the data set does span over 10 years, the researcher could not identify which courses (e.g., core courses for the program curriculum), regardless of delivery format, had been required for each academic major. Changes of required courses, course title changes, and course descriptions were in some cases not well documented. To attempt to identify required courses would have led to inconsistent interpretation by the researcher. Therefore, the study examined all courses and did not indicate which courses were required for each academic major. Courses were nested by academic school/college but not by academic program because there was no variable, consistent or otherwise, that clearly identified which courses were core courses, required for degree completion.

INDEPENDENT VARIABLES (IV).

The following table lists the variables available in the database at the private, four-year northeastern institution (see Table 3 below). This table was devised based on a review of the literature (discussed in Chapter 2) and control variables (demographic and academic performance) were selected. For a complete listing of all the independent variables used in this study (codebook), please see Appendix B.

Table 3. Independent Variables

Demographics
Age (*type of variable)*
▪ 18-43 (undergraduate students)
Gender *(nominal, dichotomous variables)*
▪ Female
▪ Male
Race/Ethnicity *(nominal variable)*
▪ American Indian
▪ Asian Pacific Islander
▪ Black African American
▪ Hispanic
▪ Non-Hispanic Multicultural
▪ Non-Resident Alien
▪ Unknown
▪ White
Financial Aid *(nominal variable)*
▪ Applied, but no need for aid
▪ Did not use financial aid
▪ Quartile 1: $0 < 17652$
▪ Quartile 2: $17652 \leq 26174$
▪ Quartile 3: $26174 \leq 34242$
▪ Quartile 4: $34242 \leq \infty$
Academic Performance
▪ Grade Point Average (GPA) Prior to Enrollment at Institution
▪ Concurrent Enrollment Programs (CEP)
▪ Scholastic Aptitude Test (SAT)
▪ Math
▪ Verbal

DEPENDENT VARIABLES (DV). The analysis in this study examines the relationship of online course participation to the following dependent variables:

Dropout. This is an indicator variable to measure dropping out (students who do not persist) of a course (regardless of delivery format) before course completion. A dropout is defined as a student who enrolls in a course but drops out prior to the course end date. The variable specifies Dropout = 1 if the student did not persist to the course end date; Dropout = 0 is specified otherwise.

Course completion. This is an indicator variable to measure course persistence in the course (regardless of delivery format) for which the student is enrolled. The variable specifies Persistence = 1 if the student completed the online course, 0 otherwise.

Performance. Aragon and Johnson (2008) define online course completion as having earned a grade of A, B, C, or D for undergraduate students. In their study grades were used not to measure student performance in an online course but to offer a clear definition of course completion. The present study examined grades in online courses and the face-to-face course equivalents for undergraduate students.

Just because a student completes an online course or a face-to-face equivalent and earns a course grade, does not mean the student has been successful (Ball State University, 2014). For this study, the grades of A thru F were used, and grade point averages ranged from 0 to 4.

Undergraduate students who completed a course were considered to have done so successfully if the student earned a grade of C or better (Performance = 1) (Ball State University, 2014). An undergraduate student who completed a course and earned a grade of D or less was considered unsuccessful (Performance = 0) (Ball State University, 2014).

Statistical Methods

In November 2013 Institutional Review Board approval was obtained to access the data from the university's student records system (see Appendix C for Institutional Review Board approval). The university student records system (SRS) data are considered to be the university's "official records" (Srinivas, 2012). The data sets used in this research were reliant on the accuracy of the university student database and the information reported therein (Srinivas, 2012). The data for this study were maintained in the PeopleSoft enterprise-level records and transaction system and were made available through the university data warehouse via querying and extraction (Srinivas, 2012). Contained in SRS are student academic performance records (transcript data), demographic information, and information about student characteristics related to performance and achievement, including enrollment and participation in online courses (Srinivas, 2012).

Working with the Office of Institutional Research (OIR), the researcher accessed these student files, which had been extracted from the SRS database. Any student identifiers, including name and university identification number, were removed from the data set prior to its release for use in this study. The subjects in this study were assigned a unique identification number, ensuring that information on individual student performance could not be linked back to the student. There were no identifying factors other than race and gender.

The data utilized in this research already existed, raising concerns about validity and reliability (Babbie, 1998). To handle validity challenges, this study ensured that complete information for each variable was available for each student included in the study. Through a frequency analysis, it was determined that no data were missing for all 42,280 records from fall

2002 to spring 2013. For each of the 42,280 records, valid values were recorded in the SRS database for both independent and dependent variables.

As regards the reliability of the data, the university's enterprise student systems maintain data integrity in three ways. First, the basic system infrastructure is built with technology that includes layers of redundancy to ensure that data are not lost or corrupted (Srinivas, 2012). Second, the system itself uses validation rules where appropriate to validate data entered into the system. Finally, business procedures within the university, the registrar's office, and the information technology support unit are designed to ensure that institutional data are entered, changed, or deleted by authorized personnel only. The system security processes are audited once a year (Srinivas, 2012).

MULTILEVEL MODELING AND EQUATIONS. MLM was selected because the nature of the data set was multilevel; therefore, the use of a single-level methodology, such as linear regression, would not have provided as accurate results. A MLM analysis was conducted to assess whether the predictor variables (i.e., age, gender, race/ethnicity, financial aid, GPA, SAT, and CEP) had a statistically significant relationship to a student's persistence and performance in online courses and the face-to-face courses. All tests were conducted at the p = <.05 level of significance. Predictor variables were entered in the same block for each model (see Table 4 for predictor variables)

Table 4. Predictor Variables Step Analysis

Undergraduate Student Population
Step 1: Age
Step 2: Gender
Step 3: Race/Ethnicity
Step 4: Financial Aid
Step 5: GPA
Step 6: SAT
Step 7: CEP

Additionally, the hierarchy consisted of units grouped at different levels. For this study there were two levels; the first-level unit was the individual student, clustered or nested in the second-level unit, which was the academic school/college. A visual representation appears in Figure 4 above.

This methodology has several advantages. First, it enables the researcher to obtain statistically efficient estimates of regression coefficients (Goldstein, 2011). Next, by using the clustering data it provides correct "standard errors, confidence intervals and significance tests and these generally will be more 'conservative' than the traditional ones that are obtained by simply ignoring the process of clustering" (Goldstein, 2011, p. 3). With covariates measured at any of the levels of the hierarchy, the researcher could determine the extent to which differences in student performance in courses could be accounted for by factors such as student characteristics.

Consider first a simple, single-level model for academic school/college relating to persistence:

$$\ln\left[\frac{p_{tj}(Y=1)}{1-p_{tj}(Y=1)}\right] = \alpha_j + \beta_{1j}X_{1j} + \cdots + \beta_{kj}X_{kj}, t = 1, \ldots, T; j = 1, \ldots, n.$$

where j indicates the individual student, t represents the course/time and standard interpretations can be given to the intercept (α), and slope for predictor Xj (β_j). It is assumed that the residuals follow a normal distribution with a zero mean and common variance (Goldstein, 2011).

To add the nested structure of students within each academic school/college, a random intercept for each academic school/college was added, represented by the subscript *t.*

$$\ln\left[\frac{p_{tj}(Y=1)}{1-p_{tj}(Y=1)}\right] = \alpha + \beta_{1j}X_{1j} + \cdots + \beta_{kj}X_{kj} + \varsigma_j, t = 1, \dots, T; j = 1, \dots, n; \varsigma_j \sim N\left(0, \sigma_\varsigma^2\right).$$

The model described above does not include repeat measures, and academic school/college is a random effect. This is now a formal model where *t* refers to the level 2 unit (academic school/college) and *j* to the level 1 unit (student) where ς_j is the random intercept, varying over academic school/colleges.

The fixed part of the model is equivalent to that of a linear regression; an outcome variable is predicted as a function of a linear combination of one or more level 1 variables, plus an intercept α, β_k represents the slope of variable X_k and e_{ij} represents the error term for the individual *i* within group *j*. In other words:

Y_{ij} represents the predicted persistence (dropout) of a course;

X_1 represents age; X_2 represents gender, X_3 represents race/ethnicity, X_4 represents financial aid, X_5 represents undergraduate GPA, X_6 represents SAT, X_7 represents CEP

The random part, ς_j represents the j^{th} college deviation from the population mean intercept represented by α.

The data set in this study has the same student taking multiple classes; therefore, each class taken by the same student must be treated as a repeated measure. For the sake of simplicity and to see the effect of each particular academic schools/college, which was treated as a fixed effect. Therefore level 1 is defined by time or occasion and level 2 by student. This model is written as follows:

$$Y_{ij} = \alpha + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots \beta_k X_{kij} + \beta_{k+1} I_1 + \beta_{k+2} I_2 + \ldots + \beta_{k+l-1} I_{l-1} + \varsigma_j + e_{ij}$$

$$e_{ij} \sim N\,(0, \sigma^2_e),\ \varsigma_j \sim N\,(0, \sigma^2_u),$$

where and e_{ij} and ς_j are assumed to be independent of each other.

Each subject, in this case the individual student, has their own intercept, also known as random intercept, which represents the j^{th} individual deviation from the population mean intercept represented by α.

The fixed effects for academic school/college are represented for the dummy variables or indicators I, where as many as the number of academic schools/colleges minus one are created. The coefficients β_{k+1} to β_{k+l-1} represent each individual academic school/college deviation from the average for the academic school/college of reference.

There is no restriction on the number of classes a student can take, so that one can apply a single model to subjects who may have participated in one or more courses.

Through this process, the researcher can accurately model the effects of the level 1 variable on the outcome and the effects of the level 2 variable on the outcome. This research design is not experimental and does not control for all pre-existing characteristics such as course selection choice. It does not make any cause and effect claims.

Strengths of Multilevel Modeling

This methodology has several advantages:

1. It enables the researcher to obtain statistically efficient estimates of regression coefficients (Goldstein, 2011).

2. By using the clustering data it provides correct “standard errors, confidence intervals and significance tests and these in general will be more ‘conservative’ than the traditional ones that are obtained by simply ignoring the process of clustering” (Goldstein, 2011, p. 3).
3. With covariates measured at any of the levels of the hierarchy, it enables the researcher to explore the extent to which differences in student performance in course offerings are accountable for by factors such as course delivery mode or other characteristics of the students.

Limitations of Multilevel Modeling

Following are limitations of this study:

1. The data set was narrowed to include fall and spring semesters within an academic year even though online courses were offered during different times of the year.
2. Due to the lack of a clear definition of online courses at the private, four-year northeastern university, only online courses offered from fall 2010 were included.
3. An assumption was made that students who enrolled in 2002 were not very different from students who enrolled in 2013, which may not be the case.

Conclusion

These first three chapters established a sound theoretical framework from which a testable model was derived. Chapter 1 defined the problem. Chapter 2 provided a systematic and comprehensive review of the current state of the literature, providing evidence of the appropriateness of the methodological selection discussed in Chapter 3. In this chapter a detailed outline of the design consideration, data collection, and analytical procedures took place. A logical chain of reasoning follows through each chapter, providing a credible and rational argument for conducting the study.

CHAPTER 4: RESULTS

The purpose of this study, conducted at a four-year private northeastern university, was to identify student characteristics that predict student persistence and performance in online courses and the face-to-face course equivalents, while controlling for many available demographic and academic-performance independent variables, using multilevel modeling (MLM). The first three chapters established a theoretical framework from which a testable model was derived. This model accounted for many available student characteristics at the private four-year northeastern institution and offered a methodological and analytical approach well suited to answer the set of research questions posed. This chapter is organized according to the procedure outlined in Chapter 3: first a description of how the data were cleaned for analysis, a sample descriptive, an overview of the models, results presented by model, research questions, and finally the conclusion.

Data Cleanup and Preparation

The total population for the original data set was 50,984. Upon preliminary analysis of the data, it was discovered that a large number of students were dropping courses at a high rate either prior to the start date of the semester or up to eight days into the semester. Upon further examination of the institution's academic calendar, it was discovered that students could add and drop courses without penalty up to eight days from the start of the semester (see Table 5 below). For semesters spanning from fall 2002 to fall 2006 the academic calendar was available but the add date was not. Examining the add date deadlines of the calendars that were available, it was apparent that, on average, the institution gave students eight days to drop a course without penalty. For semesters spanning from fall 2002 to fall 2006 it was decided that the add deadline would be assumed to be eight days. The students who dropped courses during the add period were removed from this study because it was assumed that the students dropped the courses to make adjustments to their schedule, not because of the course or for personal reasons. Thus, a total of 8,433 student records were removed. The total number of records in the data set was thus reduced to 42,551.

Table 5. Add Class Deadline

Term	First Day of Classes	Add Class Deadline	Days
Fall 2007	27-Aug	4-Sep	8
Spring 2008	14-Jan	22-Jan	8
Fall 2008	25-Aug	2-Sep	8
Spring 2009	12-Jan	20-Jan	8
Fall 2009	31-Aug	8-Sep	8
Spring 2010	19-Jan	26-Jan	7
Fall 2010	30-Aug	7-Sep	8
Spring 2011	18-Jan	25-Jan	7
Fall 2011	29-Aug	6-Sep	8
Spring 2012	17-Jan	24-Jan	7
Fall 2012	25-Aug	4-Sep	8
Spring 2013	14-Jan	22-Jan	8
Fall 2013	26-Aug	3-Sep	8
Spring 2014	13-Jan	21-Jan	8

Data Set Features

In the data set there were eight race/ethnicity codes; (a) American Indian, (b) Asian Pacific Islander, (c) Black African American, (d) Hispanic, (e) Non-Hispanic Multicultural, (f) Non-Resident Alien, (g) Unknown, and (h) White. There were 114 individuals who did not identify their race/ethnicity. These individuals were grouped into the Unknown code category. The data used in this study spans from fall 2002 to spring 2013. The entire population (100%) was comprised of undergraduate students, and all courses were delivered either during the fall or spring semester.

Students who enrolled in courses could have received grades other than A thru F or been assigned other codes that indicate incomplete, audit, pass/fail, in progress, etc. In Table 6 below all grading codes recognized by the registrar at the institution are explained.

Table 6. Grading Codes as Identified and Defined by the Institution

Grading Symbol	Meaning	Grade Points Per Credit	Explanation
I	Incomplete	0	Indicates that, due to exceptional circumstances, a student has made a formal arrangement with the instructor to complete remaining work/assignments after the course ends.
AU	Audit	Not counted	Indicates that a student elected to take the course for no (zero) credit.
NA	Did not attend and did not withdraw	Not counted	Indicates that a student never attended the course, or that participation ended so early in the term that there was no basis for evaluation.
NR	Not Required	Not counted	Used for courses or components of courses that do not require a grade.
P	Pass	Not counted	Indicates satisfactory completion of a Pass/Fail-graded course or one for which a student elected the Pass/Fail option.
RM	Remedial	Not counted	Used for college-level remedial and developmental courses.
V	Variable length course—grade not yet due	Not counted	Used for courses that do not follow the normal semester timeline. “V” indicates that normal progress is being made at the end-of-semester point.
WD	Withdrew	Not counted	Indicates that a student withdrew from the course after the academic drop deadline.

In the data set, one student (n = 1) audited a course, two students (n = 2) received incompletes, 250 took courses and did not attend/withdraw (NA), and two students (n = 2) participated in courses that were of variable length (used to denote courses that do not follow the normal semester timeline. “V” indicates that normal progress is being made at the end-of-semester point). These data were not used in the final data set as the researcher could not reasonably determine if the students who received these codes persisted or not. The total number of records in the data set was again reduced, this time to 42,296.

The data set contained 16 records that had no grade assigned and no drop date entered. Upon further investigation, no reasonable explanation could be provided about why this happened. Therefore these 16 records were removed for a data set of 42,280 (25,167 unduplicated students). These 42,280 records were used in the final analysis responding to the research questions.

Descriptive Statistics

This section provides sample descriptive statistics regarding the 42,280 records used in the final analysis. A narrative of the data is provided, along with a table of the statistics broken out by overall dropout, then dropout by gender, race/ethnicity, academic school/college, financial aid need, and age, as well as by course delivery mode (online or face-to-face). Then a frequency table of the grade distribution by online and face-to-face courses is provided, followed by the total number of students enrolled each academic year by course mode (online or face-to-face). This format is then repeated with a population of students who had participated in concurrent enrollment programs (CEP) prior to enrollment at the institution.

Overall Dropout

The overall population was 42,280. Within this population, 6.94% (n = 2,935) observations dropped out of a course, regardless of delivery format. A total of 1,482 observations corresponded to students who enrolled in online courses; 14.24% (n = 211) dropped and 85.76% (n = 1,271) did not drop the online course. A total of 40,798 observations belonged to students enrolled in face-to-face courses, and 6.68% (n = 2,724) dropped and 93.32% (n = 38,074) did not drop the face-to-face courses. See Table 7 below.

Table 7. Overall Dropout for Online and Face-to-Face Courses

Variables	Online		Face-to-Face		Overall Population	
	n=1482	%	n=40798	%	n=42280	%
Dropout	211	14.24	2724	6.68	2935	6.94
Did Not Dropout	1271	85.76	38074	93.32	39345	93.06

These data suggest that, overall, about 7% of students in this sample dropped out of courses after enrollment dates had ended, and that this held true for both online and face-to-face courses; however, dropout rated for online courses appeared to be more than double the rate for face-to-face courses.

Gender

Within the population, there were a total of 22,368 female observations and 19,912 male observations. Female observations (n = 1,398, 47.63%) dropped out of courses, regardless of the delivery format, more than male observations (n = 1,537, 53.37%) did. See Table 8 below.

Table 8. Overall Dropout by Gender

Variables	Dropped Overall		Did Not Drop Overall		Overall Population	
	n=2935	%	n=39345	%	n=42280	%
Female	1398	47.63	20970	53.30	22368	52.90
Male	1537	52.37	18375	46.70	19912	47.10

These data suggest that, overall, there were slightly more females in the data set than males, and that overall dropout rates for females was lower than males.

For online courses a total of 907 female observations and 575 male observations enrolled. A total of 130 (14.33%) female observations dropped out of the online course, and 81 (14.09%) male observations dropped out of the online course. For face-to-face courses, a total of 21,461 female observations and 19,337 male observations enrolled. A total of 1,268 (5.91%) female observations dropped out of a face-to-face course and 1,456 (7.53%) male observations dropped out of a face-to-face course. See Table 9 below.

Table 9. Dropout by Gender in Online and Face-to-Face Courses

Variables	Online Population		Dropped Online		Did Not Drop Online		Face-to-Face Population		Dropped Face-to-Face		Did Not Drop Face-to-Face	
	n=1482	%	n=211	%	n=1271	%	n=40798	%	n=2724	%	n=38074	%
Female	907	61.20	130	14.33	777	85.67	21461	52.60	1268	5.91	20193	94.09
Male	575	38.80	81	14.09	494	85.91	19337	47.40	1456	7.53	17881	92.47

These data suggest that, overall, there were more females in the data set enrolled in online courses than males, and they dropped out of online courses slightly more than males did. For face-to-face courses the opposite is true; these data suggest that slightly more males dropped face-to-face courses than females did, even though females enrolled in face-to-face courses slightly more than males.

Race/Ethnicity

The United States Census Bureau (2015) defines race/ethnicity as “an individual’s response to the race question which is based upon self-identification.” The data collected in the institution’s warehouse aligns with the classifications identified by the United States Census Bureau (2015): White, Black African American; American Indian; Asian and Pacific Islander.

White (n = 26,627, 62.98%) was the largest group in terms of race/ethnicity represented in the sample. Asian Pacific Islander (n = 3,922, 9.28%) was the second largest, and the smallest group represented in the sample was American Indian (n = 226, .53%). White students had the highest dropout rate, with 50.19% (n = 1,473) overall, followed by Asian Pacific Islander, with 11.79% (n = 346). The race/ethnicity American Indians (1.16%, n = 34) had the lowest percentage of dropout overall. See Table 10 below.

Table 10. Overall Dropout by Race/Ethnicity

Variables	Dropped		Did Not Drop		Overall Population	
	n=2935	%	n=39345	%	n=42280	%
White	1473	50.19	25154	63.93	26627	62.98
American Indian	34	1.16	192	0.49	226	0.53
Asian Pacific Islander	346	11.79	3576	9.09	3922	9.28
Black African American	312	10.63	3010	7.65	3322	7.86
Hispanic	339	11.55	3133	7.96	3472	8.21
Non-Hispanic Multicultural	50	1.70	412	1.05	462	1.09
Non-Resident Alien	155	5.28	943	2.40	1098	2.60
Unknown	226	7.70	2925	7.43	3151	7.45

These data suggest that, overall, there were more White students that enrolled in courses than other races/ethnicities, and White students dropped out of courses, regardless of delivery format (online or face-to-face), more than other races/ethnicities did.

In online courses, the largest enrolled group was White students (n = 888), but those students who identified as Unknown had the lowest dropout rate (4.88%, n = 4). The group with the largest dropout rate in online courses was American Indian students (57.14, n = 4).

For face-to-face courses, the largest enrolled group was White students (n = 25,739), and White students also had the lowest dropout rate in face-to-face courses (5.36%, n = 1,380). The group with the largest dropout rate in face-to-face courses were those students who identified as American Indian (13.70, n = 30). See Table 11 below.

Table 11. Dropout by Race/Ethnicity in Online and Face-to-Face Courses

Variables	Online Population		Dropped Online		Did Not Drop Online		Face-to-Face Population		Dropped Face-to-Face		Did Not Drop Face-to-Face	
	n=1482	%	n=211	%	n=1271	%	n=40798	%	n=2724	%	n=38074	%
White	888	59.92	93	10.47	795	89.53	25739	63.09	1380	5.36	24359	94.64
American Indian	7	0.47	4	57.14	3	42.86	219	0.54	30	13.70	189	86.30
Asian Pacific Islander	119	8.03	19	15.97	100	84.03	3803	9.32	327	8.60	3476	91.40
Black African American	155	10.46	25	16.13	130	83.87	3167	7.76	287	9.06	2880	90.94
Hispanic	126	8.50	31	24.60	95	75.40	3346	8.20	308	9.21	3038	90.79
Non-Hispanic Multicultural	20	1.35	9	45.00	11	55.00	442	1.08	41	9.28	401	90.72
Non-Resident Alien	85	5.74	26	30.59	59	69.41	1013	2.48	129	12.73	884	87.27
Unknown	82	5.53	4	4.88	78	95.12	3069	7.52	222	7.23	2847	92.77

These data suggest that in both online and face-to-face courses, American Indian students were more likely to drop than other races/ethnicities in the data set.

Academic School/College

The school/college with the largest enrollment was the College of Arts and Sciences (n = 14,659, 34.67%). The College of Arts and Sciences (n = 1,076, 36.66%) also had the largest amount of student observations dropping courses, regardless of delivery format (online or face-to-face). The academic school/college with the lowest enrolled was the College of Continuing Education (n = 30, .07%), which also had the least amount of student observations who dropped out (n = 4, .14%), regardless of course delivery mode. See Table 12 below.

Table 12. Overall Dropout by Academic School/College

Variables	Dropped		Did Not Drop		Overall Population	
	n=2935	%	n=39345	%	n=42280	%
College of Arts and Sciences	1076	36.66	13583	34.52	14659	34.67
School of Education	78	2.66	1369	3.48	1447	3.42
College of Engineering and Computer Science	210	7.16	3203	8.14	3413	8.07
College of Human Ecology	107	3.65	1481	3.76	1588	3.76
College of Sport and Human Dynamics	167	5.69	2075	5.27	2242	5.30
College of Visual and Performing Arts	515	17.55	5624	14.29	6139	14.52
School of Architecture	82	2.79	761	1.93	843	1.99
School of Information Studies	191	6.51	2037	5.18	2228	5.27
School of Management	418	14.24	6782	17.24	7200	17.03
School of Public Communications	87	2.96	2404	6.11	2491	5.89
College of Continuing Education	4	0.14	26	0.07	30	0.07

These data suggest that, given all the enrolled students, the academic school/college that had the highest number of enrollments was the College of Arts and Sciences, and it also had the largest percentage of dropouts.

The College of Arts and Sciences (n = 439) had the largest number of students enrolling in online courses, and the College of Visual and Performing Arts had the highest dropout rates (20.61%, n = 34) in online courses. The College of Continuing Education had no students drop out of online courses (0%, n = 5), and the College of Engineering and Computer Science had the second lowest dropout rate (6.56, n = 4) in online courses.

Regarding face-to-face courses, the College of Arts and Sciences (n = 14,220) had the largest number of students enrolling in face-to-face courses, and the College of Continuing Education (16.00%, n = 4) had the highest dropout rates in face-to-face courses. The School of Public Communications (2.98%, n = 67) had the lowest dropout rate in face-to-face courses. See Table 13 below.

Table 13. Dropout by Academic School/College in Online and Face-to-Face Courses

Variables	Online Population		Dropped Online Course		Did Not Drop Online Course		Face-to-Face Population		Dropped Face-to-Face Course		Did Not Drop Face-to-Face Course	
	n=1482	%	n=211	%	n=1271	%	n=40798	%	n=2724	%	n=38074	%
College Arts and Sciences	439	29.62	77	17.54	362	82.46	14220	34.85	999	7.03	13221	92.97
School of Education	30	2.02	2	6.67	28	93.33	1417	3.47	76	5.36	1341	94.64
College of Engineering and Computer Science	61	4.12	4	6.56	57	93.44	3352	8.22	206	6.15	3146	93.85
College of Human Ecology	72	4.86	10	13.89	62	86.11	1516	3.72	97	6.40	1419	93.60
College of Sport and Human Dynamics	99	6.68	16	16.16	83	83.84	2143	5.25	151	7.05	1992	92.95
College of Visual and Performing Arts	165	11.13	34	20.61	131	79.39	5974	14.64	481	8.05	5493	91.95
School of Architecture	25	1.69	5	20.00	20	80.00	818	2.01	77	9.41	741	90.59
School of Information Studies	113	7.62	22	19.47	91	80.53	2115	5.18	169	7.99	1946	92.01
School of Management	230	15.52	21	9.13	209	90.87	6970	17.08	397	5.70	6573	94.30
School of Public Communications	243	16.40	20	8.23	223	91.77	2248	5.51	67	2.98	2181	97.02
College of Continuing Education	5	0.34	0	0.00	5	100.00	25	0.06	4	16.00	21	84.00

These data suggest that, given all the enrolled students, the academic school/college that had the highest number of enrollments was the College of Arts and Sciences in both online and face-to-face courses, but the College of Continuing Education had the lowest dropout rate in online courses, and the School of Public Communications had the lowest dropout rate in face-to-face courses.

Financial Aid

As mentioned in Chapter 2, financial need is an indicator of a student's general socioeconomic status. To determine need the cost of attending college is subtracted from the family's expected financial contribution (Srinivas, 2012). This study refines Srinivas's (2012) categories by using quartiles with need categories denoted by dollar amount. Quartiles were calculated by the dollar amount of the students' financial need, based on the Free Application for Federal Student Aid (FAFSA) methodology. The categories used in this study are as follows:

1. Filed application, but no need;

2. Filed application, but did not use financial aid;
3. Quartile 1 (Q1): 0 < \$17,652;
4. Quartile 2 (Q2): \$17,652 ≤ \$26,174;
5. Quartile 3 (Q3): \$26,174 ≤ \$34,242;
6. Quartile 4 (Q4): \$34,242 ≤ ∞.

Surprisingly, a large number of student observations did not file or did not need FAFSA (n = 15,986, 37.81%). On the other end of the spectrum, student observations who qualified for quartile 4 (n = 14,987, 35.45%) was the largest of all four quartiles. The student observations who dropped courses the most, regardless of delivery format, were those students who qualified for quartile 4 (n = 1,179, 40.17%). Student observations that qualified for quartile 1 dropped the least (n = 224, 7.63%) amount of courses, regardless of delivery format. See Table 14 below.

Table 14. Overall Dropout by Financial Aid Need

Variables	**Dropped**		**Did Not Drop**		**Overall Population**	
	n=2935	%	n=39345	%	n=42280	%
Filed FAFSA, Did Not Have Need OR Did not File FAFSA	1056	35.98	14930	37.95	15986	37.81
Quartile 1: 0 < 17652	224	7.63	3241	8.24	3465	8.20
Quartile 2: 17652 ≤ 26174	205	6.98	3139	7.98	3344	7.91
Quartile 3: 26174 ≤ 34242	271	9.23	4227	10.74	4498	10.64
Quartile 4: 34242 ≤ ∞	1179	40.17	13808	35.09	14987	35.45

These data suggest that, given all the enrolled students, those students who filed a FAFSA, did not have financial need, or did not file a FAFSA were the largest group, and those students who qualified for quartile 4 were the second largest group. Those students in quartile 4 dropped courses, regardless of delivery format (online or face-to-face), slightly more than the other groups.

Age

Twenty-year-old students (n = 17,110, 40.47%) comprised the largest group of observations in the data set, followed by 21-year-olds (n = 9,333, 20.07%) and then ages 16, 30, 32, 33, 35, 44, and 46 (there was only one student observation for each of these ages). See Table 15 below.

Table 15. Frequency of Population by Age

Variable	Frequency		Overall Population	
	n=42280	%	n=42280	%
16	1	0.00	1	0.00
17	45	0.11	45	0.11
18	3224	7.63	3224	7.63
19	7691	18.19	7691	18.19
20	17110	40.47	17110	40.47
21	9333	22.07	9333	22.07
22	3617	8.55	3617	8.55
23	925	2.19	925	2.19
24	168	0.40	168	0.40
25	77	0.18	77	0.18
26	43	0.10	43	0.10
27	24	0.06	24	0.06
28	11	0.03	11	0.03
29	2	0.00	2	0.00
30	1	0.00	1	0.00
32	1	0.00	1	0.00
33	1	0.00	1	0.00
35	1	0.00	1	0.00
44	1	0.00	1	0.00
45	3	0.01	3	0.01
46	1	0.00	1	0.00

These data suggest that 20-year-old students were the largest group, and the smallest group of students were ages 16, 30, 32, 33, 35, 44, and 46.

Examining age by overall dropout rate, 20-year-olds had the largest number of student observations dropping (n = 1,084, 36.93%). The 32- and 44-year-olds dropped out of the course, regardless of delivery mode. See Table 16 below.

Table 16. Overall Dropout by Age

Variable	Dropped		Did Not Drop		Overall Population	
age	n=2935	%	n=39345	%	n=42280	%
16	0	0.00	1	0.00	1	0.00
17	3	0.10	42	0.11	45	0.11
18	169	5.76	3055	7.76	3224	7.63
19	529	18.02	7162	18.20	7691	18.19
20	1084	36.93	16026	40.73	17110	40.47
21	637	21.70	8696	22.10	9333	22.07
22	328	11.18	3289	8.36	3617	8.55
23	127	4.33	798	2.03	925	2.19
24	31	1.06	137	0.35	168	0.40
25	10	0.34	67	0.17	77	0.18
26	8	0.27	35	0.09	43	0.10
27	6	0.20	18	0.05	24	0.06
28	1	0.03	10	0.03	11	0.03
29	0	0.00	2	0.01	2	0.00
30	0	0.00	1	0.00	1	0.00
32	1	0.03	0	0.00	1	0.00
33	0	0.00	1	0.00	1	0.00
35	0	0.00	1	0.00	1	0.00
44	1	0.03	0	0.00	1	0.00
45	0	0.00	3	0.01	3	0.01
46	0	0.00	1	0.00	1	0.00

These data suggest that 20-year-old students were, overall, the largest group, and the smallest groups of students were ages 16, 30, 32, 33, 35, 44, and 46.

In online courses, 21-year-olds (n = 523) enrolled the most in online courses, and 18-year-old students had the highest dropout rate in online courses (33.33%, n = 1). See Table 17 below.

Table 17. Dropout by Age in Online Courses

Variable	Overall Population		Dropped Online Course		Did Not Drop Online Course	
age	n=1482	%	n=211	%	n=1271	%
18	3	0.20	1	33.33	2	66.67
19	38	2.56	6	15.79	32	84.21
20	167	11.27	28	16.77	139	83.23
21	523	35.29	72	13.77	451	86.23
22	499	33.67	60	12.02	439	87.98
23	168	11.34	30	17.86	138	82.14
24	32	2.16	7	21.88	25	78.13
25	19	1.28	3	15.79	16	84.21
26	12	0.81	2	16.67	10	83.33
27	10	0.67	1	10.00	9	90.00
28	6	0.40	1	16.67	5	83.33
29	1	0.07	0	0.00	1	100.00
30	1	0.07	0	0.00	1	100.00
45	2	0.13	0	0.00	2	100.00
46	1	0.07	0	0.00	1	100.00

In face-to-face courses, 20-year-old students (n = 16,643) had the largest number enrolled in face-to-face courses. Students ages 32 (100%, n = 1) and 44 (100%, n = 1) had the highest dropout rate in face-to-face courses. See Table 18 below.

Table 18. Dropout by Age in Face-to-Face Courses

Variable	Overall Population		Dropped F2F Course		Did Not Drop F2F Course	
age	n=40798	%	n=2724	%	n=38074	%
16	1	0.00	0	0.00	1	100.00
17	45	0.11	3	6.67	42	93.33
18	3221	7.89	168	5.22	3053	94.78
19	7653	18.76	523	6.83	7130	93.17
20	16943	41.53	1056	6.23	15887	93.77
21	8810	21.59	565	6.41	8245	93.59
22	3118	7.64	268	8.60	2850	91.40
23	757	1.86	97	12.81	660	87.19
24	136	0.33	24	17.65	112	82.35
25	58	0.14	7	12.07	51	87.93
26	31	0.08	6	19.35	25	80.65
27	14	0.03	5	35.71	9	64.29
28	5	0.01	0	0.00	5	100.00
29	1	0.00	0	0.00	1	100.00
32	1	0.00	1	100.00	0	0.00
33	1	0.00	0	0.00	1	100.00
35	1	0.00	0	0.00	1	100.00
44	1	0.00	1	100.00	0	0.00
45	1	0.00	0	0.00	1	100.00

Grade Distribution

With regard to grade distribution, student observations received a letter grade of A- (n = 8,511, 21.64%) most frequently, regardless of course delivery format. In online courses, a grade of A (n = 405, 31.89%) was earned most frequently, and in face-to-face courses, a grade of A- (n = 8,282, 21.76%) was most frequently earned. Not many student observations in the population opted to take a course for a grade of pass or fail (n = 74, .19%). See Table 19 below.

Table 19. Grade Distribution by Online and Face-to-Face Courses

Variables	Online Course		Face-to-Face Course		Overall Population	
	n=1270	%	n=38063	%	n=39333	%
Grade of A	405	31.89	7422	19.50	7827	19.90
Grade of A-	229	18.03	8282	21.76	8511	21.64
Grade of B+	167	13.15	6386	16.78	6553	16.66
Grade of B	143	11.26	6917	18.17	7060	17.95
Grade of B-	94	7.40	3531	9.28	3625	9.22
Grade of C+	54	4.25	1450	3.81	1504	3.82
Grade of C	57	4.49	1798	4.72	1855	4.72
Grade of C-	23	1.81	789	2.07	812	2.06
Grade of D	35	2.76	729	1.92	764	1.94
Grade of F	34	2.68	714	1.88	748	1.90
Pass/Fail	29	2.28	45	0.12	74	0.19

These data suggest that, overall, a grade of A- is most frequently earned, regardless of course delivery format (online or face-to-face), but in online courses, a grade of A is earned more frequently, and a grade of A- is earned more frequently in a face-to-face course.

Academic Year

The academic year encompasses both the fall and spring semesters. For example, academic year 2002–2003 includes fall 2002 and spring 2003. It is important to note that fall and spring semesters were included because the courses offered during these semesters were delivered over the same length of time, whereas courses offered at different times may vary in length. This is the case in the summer when the institution offers courses in 12-week, six-week, or two-week formats.

Prior to the academic year 2010–2011, there were no online course offerings, as shown in Table 20 below. While the institution did offer online courses, these courses were coded in the system as World Wide Web. The institution could not explain clearly how or why courses were labeled as World Wide Web. It was not until the academic year 2010–2011 that the registrar's office began using the following codes and definitions:

1. Online Asynchronous Non-Residency Class: A class offering taught asynchronously, with students and instructors physically separated, and delivered/accessed online, primarily without scheduled class sessions or real-time interaction.
2. Online Asynchronous Residency Class: A class offering with limited-duration in-person, on-campus class meetings, followed and/or preceded by online asynchronous class delivery/access, primarily without scheduled class sessions or real-time interaction.
3. Online Synchronous Non-Residency Class: A class offering taught synchronously, with students and instructors physically separated but interacting and exchanging class content online in real-time during scheduled class sessions, having no face-to-face interactions (except as mediated by technology).
4. Online Synchronous Residency Class: A class offering with limited-duration in-person class meetings, followed and/or preceded by synchronous class delivery/access with students and instructors interacting and exchanging class content in real-time online during scheduled class sessions (that may include face-to-face interactions mediated by technology).
5. Synchronous: Students and/or instructors interact in real-time.
6. Asynchronous: Students access class content on their own time. Real-time communication among and between students and instructors is not required.
7. Residency: The physical presence of students is required in a physical campus location.

8. Non-Residency: The physical presence of students on campus is never required (Registrar, 2014).

Table 20. Number of Course Offerings by Academic Year in Online and Face-to-Face Courses

Cohort: Academic Year	Online		Face-to-Face		Overall Population	
	n=1482	%	n=40798	%	n=42280	%
Academic Year 2002–2003	0	0.00	1829	4.48	1829	4.33
Academic Year 2003–2004	0	0.00	2541	6.23	2541	6.01
Academic Year 2004–2005	0	0.00	3027	7.42	3027	7.16
Academic Year 2005–2006	0	0.00	2974	7.29	2974	7.03
Academic Year 2006 -2007	0	0.00	3466	8.50	3466	8.20
Academic Year 2007–2008	0	0.00	4037	9.90	4037	9.55
Academic Year 2008–2009	0	0.00	6179	15.15	6179	14.61
Academic Year 2009–2010	0	0.00	4048	9.92	4048	9.57
Academic Year 2010–2011	492	33.20	3927	9.63	4419	10.45
Academic Year 2011–2012	472	31.85	4429	10.86	4901	11.59
Academic Year 2012–2013	518	34.95	4341	10.64	4859	11.49

For this study, as indicated in Chapter 2, courses coded as *online asynchronous non-residency* were included in this data set. Additionally, a face-to-face course coded as *synchronously* was included in this data set. Why include data from academic years prior to 2010–2011 if there were no online course data that could be included?

This study investigated whether or not the student characteristics that predict student persistence and performance in online courses differ from those that predict student persistence and performance in the face-to-face course equivalents, while controlling for many available independent variables. Face-to-face courses were not necessarily offered every semester, let alone every academic year. This means that if a fictional course, Computational Basket Weaving 101 was most recently offered face-to-face in fall 2002 and not again until spring 2012 but the online course was offered in fall 2011, then the fall 2002 instance must be included in the data. This assumes that students who enrolled in the institution in 2003 were not very different from students who enrolled in 2013.

Descriptive Statistics for CEP

This section offers the descriptive statistics for the population that had participated in a Concurrent Enrollment Program (CEP) prior to enrollment at the institution. For the variable CEP there were only 9,439 complete observations. Including this variable in the first four models greatly reduced the data set. As a result, the first four models were run with all independent variables, as indicated in Chapter 3, except the independent variable, CEP. The researcher still found value in the 9,439 observations and chose to investigate whether CEP, as a student characteristic, had an impact on student persistence and performance in online courses and the face-to-face equivalents. Therefore the same four models were run a second time, using a subset of data (n = 9,439) that included CEP as an independent variable.

Overall Dropout

For those students who had enrolled in a CEP, 93.77% (n = 8,822) did not drop out of a course, regardless of the delivery format. A total of 357 students who had participated in a CEP prior to enrollment at the institution enrolled in an online course. Of the students who enrolled in an online course, 14.29% (n = 51) dropped out of the online course. See Table 21 below.

Table 21. Overall Dropout in Online and Face-to-Face Courses

Variables	Online		Face-to-Face		Overall Population	
	n=357	%	n=9082	%	n=9439	%
Dropout	51	14.29	566	6.23	617	6.54
Did Not Dropout	306	85.71	8516	93.77	8822	93.46

These data suggest that, overall, about 7% of students in this sample dropped out of courses after enrollment dates had ended, and that this held true for both online and face-to-face courses. However, dropout rates for online courses appeared to be more than double the rates for face-to-face courses.

Gender

More females (53.86%, n = 5,084) than males (46.14%, n = 4,355) had participated in CEP prior to enrollment at the institution. More males (51.05%, n = 315) had dropped a course, regardless of delivery format, than females (48.95%, n = 302). See Table 22 below.

Table 22. Overall Dropout by Gender

Variables	Dropped		Did Not Drop		Overall Population	
	n=617	%	n=8822	%	n=9439	%
Female	302	48.95	4782	54.21	5084	53.86
Male	315	51.05	4040	45.79	4355	46.14

These data suggest that, overall, there were slightly more females in the data set than males, and that overall dropout rates for females were less than rates for males.

In online courses, females (n = 212) who had participated in a CEP prior to enrollment at the institution enrolled in online courses more than males (n = 145). In online courses, males' (15.86, n = 122) dropout rate was slightly higher than females' (13.21%, n = 28) in online courses.

In face-to-face courses, females (n = 4,872) who had participated in a CEP prior to enrollment at the institution enrolled in online courses more than males (n = 4,210) did. In face-to-face courses, males (6.94%, n = 292) dropped more than females (5.62, n = 274). See Table 23 below.

Table 23. Dropout by Gender in Online and Face-to-Face Courses

Variables	Online Population		Dropped Online		Did Not Drop Online		Face-to-Face Population		Dropped Face-to-Face		Did Not Drop Face-to-Face	
	n=357	%	n=51	%	n=306	%	n=9082	%	n=566	%	n=8516	%
Female	212	59.38	28	13.21	184	86.79	4872	53.64	274	5.62	4598	94.38
Male	145	40.62	23	15.86	122	84.14	4210	46.36	292	6.94	3918	93.06

These data suggest that, overall, slightly more males dropped online and face-to-face courses than females, and, overall, more females enrolled in both online and face-to-face courses.

Race/Ethnicity

Overall, White students (62.50%, n = 5,899) who had participated in a CEP prior to enrollment at the institution enrolled in courses, regardless of delivery format, more than the other races/ethnicities. The second largest population was Asian Pacific Islander (9.55%, n = 901). White students (51.05%, n = 315) and Asian Pacific Islander students (11.83%, n = 73) dropped courses, regardless of delivery format, more than the other races/ethnicities in the data set. See Table 24 below.

Table 24. Overall Dropout by Race/Ethnicity

Variables	Dropped		Did Not Drop		Overall Population	
	n=617	%	n=8822	%	n=9439	%
White	315	51.05	5584	63.30	5899	62.50
American Indian	10	1.62	52	0.59	62	0.66
Asian Pacific Islander	73	11.83	828	9.39	901	9.55
Black African American	59	9.56	611	6.93	670	7.10
Hispanic	57	9.24	758	8.59	815	8.63
Non-Hispanic Multicultural	6	0.97	126	1.43	132	1.40
Non-Resident Alien	42	6.81	242	2.74	284	3.01
Unknown	55	8.91	621	7.04	676	7.16

Given all the enrolled students, White students had the highest number of enrollments and represented the largest percentage of dropouts.

In online courses, White students (n = 204) enrolled more than other races/ethnicities. Non-Resident Alien students' (50.00%, n = 5) dropout rate was the highest, and Unknown (8.33%, n = 2) was the lowest. Note, there were no American Indian students enrolled in online courses.

In face-to-face courses, White students (n = 5695) had the highest enrollments. American Indian students (16.13%, n = 10) had the highest dropout rate and Non-Hispanic Multicultural students (2.40%, n = 3) had the lowest dropout rate in face-to-face courses. See Table 25 below.

Table 25. Dropout by Race/Ethnicity in Online and Face-to-Face Courses

Variables	**Online Population**		**Dropped Online**		**Did Not Drop Online**		**Face-to-Face Population**		**Dropped Face-to-Face**		**Did Not Drop Face-to-Face**	
	n=357	%	n=51	%	n=306	%	n=9082	%	n=566	%	n=8516	%
White	204	57.14	24	11.76	180	88.24	5695	62.71	291	5.11	5404	94.89
American Indian	0	0.00	0	0.00	0	0.00	62	0.68	10	16.13	52	83.87
Asian Pacific Islander	32	8.96	3	9.38	29	90.63	869	9.57	70	8.06	799	91.94
Black African American	40	11.20	6	15.00	34	85.00	630	6.94	53	8.41	577	91.59
Hispanic	40	11.20	8	20.00	32	80.00	775	8.53	49	6.32	726	93.68
Non-Hispanic Multicultural	7	1.96	3	42.86	4	57.14	125	1.38	3	2.40	122	97.60
Non-Resident Alien	10	2.80	5	50.00	5	50.00	274	3.02	37	13.50	237	86.50
Unknown	24	6.72	2	8.33	22	91.67	652	7.18	53	8.13	599	91.87

Given all the enrolled students, White students had the highest number of enrollments, regardless of course delivery format (online or face-to-face).

Academic School/College

Students who had participated in CEP prior to enrollment at the institution enrolled in the College of Arts and Sciences (41.18%, n = 3,887) and dropped out (40.84%, n = 252) more than students in the other academic schools/colleges. See Table 26 below.

Table 26. Overall Dropout by Academic School/College

Variables	Dropped		Did Not Drop		Overall Population	
	n=617	%	n=8822	%	n=9439	%
College Arts and Sciences	252	40.84	3635	41.20	3887	41.18
School of Education	21	3.40	404	4.58	425	4.50
College of Engineering and Computer Science	46	7.46	670	7.59	716	7.59
College of Human Ecology	19	3.08	229	2.60	248	2.63
College of Sport and Human Dynamics	25	4.05	286	3.24	311	3.29
College of Visual and Performing Arts	99	16.05	1094	12.40	1193	12.64
School of Architecture	22	3.57	113	1.28	135	1.43
School of Information Studies	53	8.59	487	5.52	540	5.72
School of Management	44	7.13	1020	11.56	1064	11.27
School of Public Communications	36	5.83	882	10.00	918	9.73
College of Continuing Education	0	0.00	2	0.02	2	0.02

Given all the enrolled students, the College of Arts and Sciences had the highest number of enrollments and the largest percentage of dropout rates overall.

Students enrolled in the College of Arts and Sciences (n = 111) had the largest number of enrollments in online courses. Students enrolled in the School of Architecture (50.00%, n = 1) had the highest dropout rate in online courses, and students enrolled in the College of Continuing Education (0.00%, n = 0) had the lowest dropout rate.

Students enrolled in the College of Arts and Sciences (n = 3,776) had the largest number of enrollments in face-to-face courses. Students enrolled in the School of Architecture (15.79%, n = 21) had the highest dropout rate in face-to-face courses, and students enrolled in the College of Continuing Education (0.00%, n = 0) had the lowest dropout rate. See Table 27 below.

Table 27. Dropout by Academic School/College in Online and Face-to-Face Courses

Variables	Online Population		Dropped Online Course		Did Not Drop Online Course		Face-to-Face Population		Dropped Face-to-Face Course		Did Not Drop Face-to-Face Course	
	n=357	%	n=51	%	n=306	%	n=9082	%	n=566	%	n=8516	%
College Arts and Sciences	111	31.09	15	13.51	96	86.49	3776	41.58	237	6.28	3539	93.72
School of Education	7	1.96	1	14.29	6	85.71	418	4.60	20	4.78	398	95.22
College of Engineering and Computer Science	20	5.60	2	10.00	18	90.00	696	7.66	44	6.32	652	93.68
College of Human Ecology	6	1.68	1	16.67	5	83.33	242	2.66	18	7.44	224	92.56
College of Sport and Human Dynamics	22	6.16	2	9.09	20	90.91	289	3.18	23	7.96	266	92.04
College of Visual and Performing Arts	42	11.76	13	30.95	29	69.05	1151	12.67	86	7.47	1065	92.53
School of Architecture	2	0.56	1	50.00	1	50.00	133	1.46	21	15.79	112	84.21
School of Information Studies	28	7.84	4	14.29	24	85.71	512	5.64	49	9.57	463	90.43
School of Management	50	14.01	4	8.00	46	92.00	1014	11.16	40	3.94	974	96.06
School of Public Communications	68	19.05	8	11.76	60	88.24	850	9.36	28	3.29	822	96.71
College of Continuing Education	1	0.28	0	0.00	1	100.00	1	0.01	0	0.00	1	100.00

Given all the enrolled students, the College of Arts and Sciences had the highest number of enrollments, regardless of course delivery format (online or face-to-face), and the School of Architecture students had the highest dropout rate in both course delivery formats (online and face-to-face).

Financial Aid

At the institution, more students had a financial need in quartile 4 (38.39%, n = 3,624) than in the other three quartiles. Students who qualified for quartile 4 (38.90%, n = 240), dropped more than other students who qualified for financial aid. See Table 28 below.

Table 28. Dropout by Financial Aid Need

Variables	Dropped		Did Not Drop		Overall Population	
	n=617	%	n=8822	%	n=9439	%
Filed FAFSA & Did Not Have Need OR Did not File FAFSA	218	35.33	3295	37.35	3513	37.22
Quartile 1: 0 < 17652	47	7.62	663	7.52	710	7.52
Quartile 2: 17652 ≤ 26174	56	9.08	703	7.97	759	8.04
Quartile 3: 26174 ≤ 34242	56	9.08	777	8.81	833	8.83
Quartile 4: 34242 ≤ ∞	240	38.90	3384	38.36	3624	38.39

These data suggest that, given all the enrolled students, those students who qualified for quartile 4 made up the largest group and had a slightly higher drop rate for all courses, regardless of delivery format.

Age

For those students who had participated in a CEP prior to enrollment at the institution, the age ranged from 17 to 44. The age population with the most students was the 18-year-olds (30.70%, n = 2,898), and then the 20-year-olds (24.31%, n = 2,295). See Table 29 below.

Table 29. Frequency of Population by Age

Variable	Frequency		Overall Population	
	n=9439	%	n=9439	%
17	39	0.41	39	0.41
18	2898	30.70	2898	30.70
19	2268	24.03	2268	24.03
20	2295	24.31	2295	24.31
21	1240	13.14	1240	13.14
22	528	5.59	528	5.59
23	131	1.39	131	1.39
24	17	0.18	17	0.18
25	10	0.11	10	0.11
26	7	0.07	7	0.07
27	3	0.03	3	0.03
29	1	0.01	1	0.01
44	1	0.01	1	0.01
45	1	0.01	1	0.01

There were more students 18 years of age than other age groups identified in the data set.

Age by dropout indicates that the 19-year-olds (25.77%, n = 159) dropped out more than other age groups, regardless of delivery format, followed by 18-year-olds (24.15%, n = 149), regardless of delivery format. See Table 30 below.

Table 30. Overall Dropout by Age

Variable	Dropped		Did Not Drop		Overall Population	
age	n=617	%	n=8822	%	n=9439	%
17	3	0.49	36	0.41	39	0.41
18	149	24.15	2749	31.16	2898	30.70
19	159	25.77	2109	23.91	2268	24.03
20	132	21.39	2163	24.52	2295	24.31
21	101	16.37	1139	12.91	1240	13.14
22	49	7.94	479	5.43	528	5.59
23	16	2.59	115	1.30	131	1.39
24	3	0.49	14	0.16	17	0.18
25	2	0.32	8	0.09	10	0.11
26	2	0.32	5	0.06	7	0.07
27	0	0.00	3	0.03	3	0.03
29	0	0.00	1	0.01	1	0.01
44	1	0.16	0	0.00	1	0.01
45	0	0.00	1	0.01	1	0.01

The age group with the highest dropout rate in courses, regardless of delivery format (online or face-to-face), were students who were 19 years of age.

A total of 357 students had participated in a CEP prior to enrollment in an online course at the institution. Of those, students who were were 21 (14.38%, n = 22) and 22 (33.89%, n = 16) dropped online courses more frequently than other age groups. See Table 31 below.

Table 31. Dropout by Age in Online Course

Variable	Overall Online Population		Dropped Online Course		Did Not Drop Online Course	
Age	n=357	%	n=51	%	n=306	%
18	2	0.56	0	0.00	2	100.00
19	13	3.64	3	23.08	10	76.92
20	40	11.20	10	25.00	30	75.00
21	153	42.86	22	14.38	131	85.62
22	121	33.89	16	13.22	105	86.78
23	26	7.28	0	0.00	26	100.00
24	1	0.28	0	0.00	1	100.00
25	1	0.28	0	0.00	1	100.00

The age group with the highest dropout rate in online courses were those students who were 21 years old.

In face-to-face courses, the largest enrolled age group was 18 year olds (n = 2896). The age groups that had the highest dropout rate in face-to-face courses were 44 year olds (100.00%, n = 1) and 26 year olds (28.57, n = 2). See Table 32 below.

Table 32. Dropout by Age in Face-to-Face Course

Variable	Overall F2F Population		Dropped F2F Course		Did Not Drop F2F Course	
age	9082	%	566	%	8516	%
17	39	0.43	3	7.69	36	92.31
18	2896	31.89	149	5.15	2747	94.85
19	2255	24.83	156	6.92	2099	93.08
20	2255	24.83	122	5.41	2133	94.59
21	1087	11.97	79	7.27	1008	92.73
22	407	4.48	33	8.11	374	91.89
23	105	1.16	16	15.24	89	84.76
24	16	0.18	3	18.75	13	81.25
25	9	0.10	2	22.22	7	77.78
26	7	0.08	2	28.57	5	71.43
27	3	0.03	0	0.00	3	100.00
29	1	0.01	0	0.00	1	100.00
44	1	0.01	1	100.00	0	0.00
45	1	0.01	0	0.00	1	100.00

The age group with the highest dropout rate in face-to-face courses were those students who were 44 years old.

Grade Distribution

In online courses, students who had participated in a CEP prior to enrollment at the institution received a grade of A (31.37%, n = 96) more than any other grade on the grade scale. For face-to-face courses, students who had participated in a CEP prior to enrollment at the institution received a grade of A- (20.43%, n = 1,740) more than any other grade on the grade scale. See Table 33 below.

Table 33. Grade Distribution in Online and Face-to-Face Courses

Variables	Online Course		Face-to-Face Course		Overall Population	
	n=306	%	n=8516	%	n=8822	%
Grade of A	96	31.37	1603	18.82	1699	19.26
Grade of A-	55	17.97	1740	20.43	1795	20.35
Grade of B+	46	15.03	1409	16.55	1455	16.49
Grade of B	38	12.42	1443	16.94	1481	16.79
Grade of B-	25	8.17	852	10.00	877	9.94
Grade of C+’	9	2.94	375	4.40	384	4.35
Grade of C	8	2.61	449	5.27	457	5.18
Grade of C-	3	0.98	211	2.48	214	2.43
Grade of D	11	3.59	228	2.68	239	2.71
Grade of F	5	1.63	199	2.34	204	2.31
Pass/Fail	10	3.27	7	0.08	17	0.19

These data suggest that, overall, a grade of A- is most frequently earned, regardless of course delivery format (online or face-to-face).

Modeling

The original plan was to conduct a three-level multilevel model. This would include time or occasion as level 1, student as level 2, nested within the academic school/college, and student nested within those courses as level 3. The model was run using the statistical software package called STATA, version 13.1. The model would not, however, converge, most likely due to the large number of observations and parameters, which increases exponentially as more levels are added to the model (Goldstein, 2011).

The three-level model was modified to become a two-level model. The two-level model removed academic school/college as a level, leaving only time/occasions as level 1, nested within students as level 2. Academic schools/colleges were included as a fixed effect by adding dummy variables for each college (except for the category of reference, which was the College of Arts and Sciences).

This was not a comparison study. The two-level model allowed for four separate models to be conducted:

1. The first model analyzed the student characteristics that predicted persistence in online courses,
2. The second model analyzed the student characteristics that predicted performance in online courses,
3. The third model analyzed the student characteristics that predicted persistence in face-to-face courses, and
4. The fourth model analyzed the student characteristics that predicted performance in face-to-face courses.

In these models, academic school/college was run as a fixed effect, and student was run as a random effect. The levels of the variable academic school/college were the levels of interest to the researcher. In contrast, the variable student was viewed as providing a random sample of the levels of the variable to be generalized. In multilevel models, the levels of the nesting variable, in this case, students, were viewed as being random (Leech, Barrett, & Morgan, 2011). The various students were considered to represent a larger population of students.

Another modification was made with regard to the independent variables. The original independent variable list was as follows (see Table 34 below):

Table 34. Predictor (IV) Variables

Demographics
Age (*type of variable)*
▪ 18-43 (undergraduate students)
Gender *(nominal, dichotomous variables)*
▪ Female
▪ Male
Race/Ethnicity *(nominal variable)*
▪ American Indian
▪ Asian Pacific Islander
▪ Black African American
▪ Hispanic
▪ Non-Hispanic Multicultural
▪ Non-Resident Alien
▪ Unknown
▪ White
Financial Aid *(nominal variable)*
▪ Applied, but no need for aid
▪ Did not use financial aid
▪ Quartile 1: $0 < 17652$
▪ Quartile 2: $17652 \leq 26174$
▪ Quartile 3: $26174 \leq 34242$
▪ Quartile 4: $34242 \leq \infty$
Academic Performance
▪ Grade Point Average (GPA) Prior to Enrollment at Institution
▪ Concurrent Enrollment Programs (CEP)
▪ Scholastic Aptitude Test (SAT)
▪ Math
▪ Verbal

For the variable concurrent enrollment programs (CEP), there were only 9,439 complete observations. Including this variable in the first four models greatly reduced the data set. As a result, the first four models were run with all the independent variables except CEP. The researcher still found value in the 9,439 observations and chose to investigate whether CEP, as a student characteristic, had an impact on student persistence and performance in online courses and the face-to-face equivalents. Therefore the same four models were run again, using a subset of data (n = 9,439) that included CEP as an independent variable.

For all eight models that follow, the reference groups for each of the categorical predictors in the models were, respectively, (a) female, (b) White, (c) did not apply for or did not need financial aid, and (d) College of Arts and Sciences. In other words, the variables run in this model were compared to the gender female, the race/ethnicity of White, the financial need of none or did not apply, and students enrolled in the College of Arts and Sciences.

An odds ratio was calculated and reported in Tables 35 and 36 below. An odds ratio is a measure of association between an exposure and an outcome (Goldstein, 2011). The odds ratio represents the odds that an outcome (aka, persisting in a course) will occur given a particular exposure (e.g. Being American Indian), compared to the odds of the same outcome occurring in the absence of that exposure (Goldstein, 2011). For example, in Model 1 (see Table 35 below) American Indian students's odds of persisting is .014 (1.4%) of the odds of persistence in the reference group (white students).

Centering the variable “age” was considered and disregarded in this study. Centering means substracting a constant from every value of a variable (Goldstein, 2011). This redefines the 0 point for that predictor (e.g. age) to be what value is subtracted (Goldstein, 2011). The result shifts the scale over but retains the units (Goldstein, 2011).

For this study, the age range is from 17-45 with the majority of the students falling in the age range of 18-24. This age range aligns with the literature identifying 79% of college students as ages 18-24 in 2012 (Allen & Seaman, 2012). Included in the study were all undergraduate students which encompassed non-traditional students which accounts for the the max age of 45. More than a third of undergraduate students are over the age of 25 and over the next 10 years the adult student enrollment in college is project to grow faster than for traditional age students (Allen & Seaman, 2012). The age ranges in this study fall within the age ranges of students in the literature and therefore it was decided not to center on age.

An additional concern for this study was multicollinearity. Multicollinearity is a phenomenon in which two or more predictor variables are highly correlated, meaning that one can be linearly predicted from the other with a substantial degree of accuracy (Goldstein, 2011). In this study, the variables GPA and SAT Score have been associated with multicollinearity (Wu & Finnegan, 2005). The correlations between SAT Math, SAT Verbal and GPA were below 0.4 so the correlation index was not large enough to indicate any strong collinearity between these predictors. Therefore, each variable, SAT Math, SAT Verbal and GPA, were included in the models.

Models 1, 2, 3, and 4

This section presents the data and interpretation for the first for models (see Table 35 below), as previously described above:

1. The first model analyzed the student characteristics that predicted persistence in online courses,
2. The second model analyzed the student characteristics that predicted performance in online courses,
3. The third model analyzed the student characteristics that predicted persistence in face-to-face courses, and
4. The third model analyzed the student characteristics that predicted performance in face-to-face courses.

Table 35. Results for Models 1, 2, 3, and 4

	Model 1: Online Persistence		Model 2: Online Performance		Model 3: Face-to-Face Persistence		Model 4: Face-to-Face Performance	
	Coefficient (P>|z|)	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**
Demographics								
Male	0.072 (0.771)	1.075	-0.324 (0141)	0.723	-0.187 (0.001)*	0.829	-0.457 (0.000)*	0.633
Age	0.073 (0.380)	1.076	-0.132 (0.064)	0.876	-0.067 (0.003)*	0.935	0.021 (0.252)	1.022
American Indian	-4.247 (0.004)*	0.014	-4.013 (0.005)*	0.018	-1.090 (0.000)*	0.336	-1.226 (0.000)*	0.293
Asian Pacific Islander	-0.225 (0.603)	0.798	-0.313 (0.434)	0.731	-0.493 (0.000)*	0.611	-0.578 (0.000)*	0.561
Black African American	-0.462 (0.271)	0.630	-1.150 (0.002)*	0.317	-0.479 (0.000)*	0.620	-0.522 (0.000)*	0.593
Hispanic	-1.011 (0.010)*	0.364	-0.998 (0.007)*	0.375	-0.557 (0.000)*	0.573	-0.618 (0.000)*	0.539
Non-Hispanic/Multicultural	-2.824 (0.000)*	0.059	-3.535 (0.000)*	0.029	-0.414 (0.083)	0.661	-0.689 (0.000)*	0.502
Non-Resident Alien	-1.372 (0.010)*	0.254	-0.974 (0.047)*	0.378	-1.050 (0.000)*	0.350	-1.121 (0.000)*	0.326
Unknown	0.872 (0.163)	2.393	0.088 (0.845)	1.091	-0.312 (0.002)*	0.732	-0.239 (0.008)*	0.788
Financial Need								
need_q1 - 0 < $17,652	-0.024 (0.961)	0.977	-0.220 (0.587)	0.802	-0.097 (0.371)	0.908	-0.106 (0.245)	0.899
need_q2 - $17,652 ≤ $26,174	-0.743 (0.101)	0.476	-0.551 (0.171)	0.576	-0.107 (0.333)	0.898	-0.124 (0.185)	0.884
need_q3 - $26,174 ≤ $34,242	0.020 (0.970)	1.020	-0.137 (0.766)	0.872	-0.094 (0.335)	0.910	-0.068 (0.411)	0.940
need_q4 - $34,242 ≤ ∞	-0.131 (0.671)	0.877	0.100 (0.716)	1.105	-0.229 (0.002)*	0.795	-0.224 (0.000)*	0.799
Academic Performance								
GPA Prior to Enrollment at Institution	0.619 (0.035)*	1.858	0.605 (0.019)*	1.832	0.840 (0.000)*	2.317	1.165 (0.000)*	3.206
SAT Math Score	-0.004 (0.039)*	0.996	-0.004 (0.041)*	0.996	-0.002 (0.000)*	0.998	-0.000 (0.305)	1.000
SAT Verbal Score	0.000 (0.867)	1.000	-0.001 (0.541)	0.999	0.001 (0.040)*	1.001	0.001 (0.001)*	1.001

	Model 1: Online Persistence		Model 2: Online Performance		Model 3: Face-to-Face Persistence		Model 4: Face-to-Face Performance	
	Coefficient (P>|z|)	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**
Academic School/College								
School of Education	1.229 (0.313)	3.418	0.292 (0.754)	1.339	0.122 (0.450)	1.130	0.214 (0.120)	1.238
College of Engineering and Computer Science	2.014 (0.013)*	7.490	1.830 (0.005)*	6.236	0.319 (0.002)*	1.376	0.291 (0.001)*	1.338
College of Human Ecology	0.189 (0.788)	1.208	0.427 (0.536)	1.533	0.083 (0.670)	1.086	-0.014 (0.931)	0.987
College of Sport and Human Dynamics	-0.110 (0.846)	0.896	-0.565 (0.258)	0.568	0.333 (0.019)*	1.395	0.095 (0.384)	1.100
College of Visual and Performing Arts	-0.204 (0.560)	0.815	-0.672 (0.032)*	0.511	-0.176 (0.025)*	0.839	-0.041 (0.546)	0.960
School of Architecture	-0.264 (0.710)	0.768	-0.571 (0.363)	0.565	-0.315 (0.049)*	0.730	-0.425 (0.002)*	0.654
School of Information Studies	0.048 (0.913)	1.049	0.077 (0.845)	1.080	0.157 (0.211)	1.170	0.037 (0.721)	1.038
School of Management	0.813 (0.029)*	2.255	0.844 (0.011)*	2.326	0.290 (0.001)*	1.337	0.556 (0.000)*	1.744
School of Public Communications	0.682 (0.071)*	1.978	0.646 (0.054)	1.908	0.575 (0.000)*	1.776	0.314 (0.010)*	1.369
College of Continuing Education	16.040 (0.998)	9246058.000	16.369 (0.998)	1.90E+70	-1.865 (0.091)	0.155	-2.032 (0.060)	0.131
ln(L0)	-600		-740		-9780		-14640	
ln(LM)	-432		-516		-7784		-11467	
pseudo R^2	0.2800		0.3027		0.2041		0.2167	

* The p-value used to discern statistical significance was 0.05.
L0: likelihood of the model with no predictors, only the constant.
LM: likelihood of the estimated model.

MODELS 1 AND 2. The first model examined the student characteristics that predicted persistence in online courses, and the second model examined the student characteristics that predicted performance in online courses. Performance for this study meant successfully completing an online or face-to-face course with a grade of C or better for undergraduate students (Ball State University, 2014). The researcher hypothesized that (a) male students would be less likely to persist and perform in online courses, (b) a student's age would not be statistically significant in predicting whether or not a student would persist and/or perform in online courses, (c) that some races/ethnicities would be less likely to persist and perform in online courses than those students who identified as White, (d) financial aid would not be statistically significant in predicting whether or not a student would persist and/or perform in online courses, (e) GPA prior to enrollment at the institution would be statistically significant in predicting student persistence and performance in online courses, (f) SAT Math scores would be statistically significant in predicting student persistence and/or performance in online courses, and (g) students who enrolled in the College of Arts and Sciences would be less likely to persist and perform in an online course than students enrolled in other schools/colleges.

For model 1, results showed that:

- Students who identified their race/ethnicity as American Indian (odds ratio = .014, p = .004), Hispanic (odds ratio = .364, p = .010), Non-Hispanic/Multicultural (odds ratio = .059, p = .000), and Non-Resident Alien (odds ratio = .254, p = .010) were less likely to persist in online courses than White students.
- The higher a student's GPA prior to enrollment at the institution, the more likely the student was to persist in online courses (odds ratio = 1.858, p = .035)
- Students with higher SAT Math Scores (odds ratio = .996, p = .039) were less likely to persist in online courses.
- Students enrolled in the College of Engineering and Computer Science (odds ratio = 7.490, p = .013), the School of Management (odds ratio = 2.255, p = .029), and the School of Public Communications (odds ratio = 1.978, p = .071) were more likely to persist in an online course than students enrolled in the College of Arts and Sciences.

The McFadden's pseudo R^2 value measures the goodness of fit, mirroring how the R^2 of a linear regression measures how close the data were to the fitted regression line (Goldstein, 2011). In other words, R^2 equals the explained variation divided by the total variation (R^2 = explained variation/total variation) and is always between 0 and 100% (Goldstein, 2011). An R^2 value of 0% indicates that the model explains none of the variability of the response data around its mean.

An R^2 value of 100% indicates that the model explains all the variability of the response data around its mean. In general, the higher the R^2 value, the better the model fits the data.

When interpreting McFadden's R^2 it is important to note proportional reduction in the error variance or percentage of variability explained by the predictors. In particular, when computing McFadden's R^2, the log likelihood of the intercept model is treated as a total sum of squares, and the log likelihood of the full model is treated as the sum of squared errors. Additionally, the clustering nature of the data has been used in the calculation of the null model (with no predictors), therefore the value examines the gain in likelihood due to the predictors (including academic school/college as it is a fixed effect). For model 1, the pseudo R^2 value is 28.0%, which means that the model accounted for 28.0% of the variance.

For model 2, the pseudo R^2 value is 30.3%, which means that the model accounted for 30.3% of the variance. The results showed that:

- Students who identified their race/ethnicity as American Indian (odds ratio = .018, p = .005), Black African American (odds ratio = .317, p = .002), Hispanic (odds ratio = .375, p = .007), Non-Hispanic/Multicultural (odds ratio = .029, p = .000), and Non-Resident Alien (odds ratio = .378, p = .047) were less likely to perform in online courses compared to White students.
- The higher a student's GPA prior to enrollment at the institution, the better the student performed in online courses (odds ratio = 1.832, p = .019).
- Students with higher SAT Math Scores (odds ratio = .996, p = .041) were less likely to perform in online courses.
- Students enrolled in the College of Engineering and Computer Science (odds ratio = 3.236, p = .005), and the School of Management (odds ratio = 2.326, p = .011) were

more likely to perform in an online course compared to students enrolled in the College of Arts and Sciences. However, students enrolled in the College of Visual and Performing Arts (odds ratio = .511, p = .032) were less likely to perform in an online course compared to students enrolled in the College of Arts and Sciences.

MODELS 3 AND 4. The third model examined the student characteristics that predicted persistence in face-to-face courses, and the fourth model examined the student characteristics that predicted performance in face-to-face courses. Performance for this study meant successfully completing an online or face-to-face course with a grade of C or better for undergraduate students (Ball State University, 2014). The researcher hypothesized that (a) male students would be less likely to persist and perform in face-to-face courses, (b) a student's age would not be statistically significant in predicting whether or not a student would persist and/or perform in face-to-face courses, (c) some races/ethnicities would be less likely to persist and perform in face-to-face courses than those students who identified as White, (d) financial aid would not be statistically significant in predicting whether or not a student would persist and/or perform in face-to-face courses, (e) GPA prior to enrollment at the institution would be statistically significant in predicting student persistence and performance in face-to-face courses, (e) SAT Math scores would be statistically significant in predicting student persistence and/or performance in face-to-face courses, and (6) students who enrolled in the College of Arts and Sciences would be less likely to persist and perform in a face-to-face course than students enrolled in other schools/colleges.

For model 3, the pseudo R^2 value was 20.4%, which means that the model accounted for 20.4% of the variance. The results showed that:

- Gender may affect persistence in face-to-face courses (male<female, odds ratio = .829, p = .001). In other words, male students were less likely to persist compared to female students.
- Older students were less likely to persist in face-to-face courses (odds ratio = .935, p = .003).
- Students who identified their race/ethnicity as American Indian (odds ratio = .336, p = .000), Asian Pacific Islander (odds ratio = .611, p = .000), Black African American (odds ratio = .620, p = .000), Hispanic (odds ratio = .573, p = .000), Non-Resident Alien (odds ratio = .350, p = .000) and Unknown (odds ratio = .732, p = .002) were less likely to persist in face-to-face courses compared to White students.
- Students who had a financial need in the fourth quartile (odds ratio = .795, p = .002) of $34,242 or more were less likely to persist in face-to-face courses compared to the students with no financial need.
- The higher a student's GPA prior to enrollment at the institution, the more likely the student was to persist in face-to-face courses (odds ratio = 2.317, p = .000)
- Students with higher SAT Math Scores (odds ratio = .998, p = .000) were less likely to persist, and students with higher SAT Verbal Scores (odds ratio = 1.001, p = .040) were more likely to persist in face-to-face courses.
- Students enrolled in the College of Engineering and Computer Science (odds ratio = 1.379, p = .002), the College of Sport and Human Dynamics (odds ratio = 1.395, p = .019), the School of Management (odds ratio = 1.337, p = .001), and the School of Public Communications (odds ratio = 1.776, p = .000) were more likely to persist in a face-to-face course compared to students enrolled in the College of Arts and

Sciences. However, students enrolled in the College of Visual and Performing Arts (odds ratio = .839, p = .025) and the School of Architecture (odds ratio = .730, p = .049) were less likely to persist in a face-to-face course compared to students enrolled in the College of Arts and Sciences.

For model 4, the pseudo R^2 value is 21.7%, which means that the model accounted for 21.7% of the variance. The results showed that:

- Gender may affect performance in face-to-face courses (male<female, odds ratio = .829, p = .001). In other words, male students were less likely to perform compared to female students.
- Students who identified their race/ethnicity as American Indian (odds ratio = .293, p = .000), Asian Pacific Islander (odds ratio = .561, p = .000), Black African American (odds ratio = .593, p = .000), Hispanic (odds ratio = .539, p = .000), Non-Hispanic/Multicutlural (odds ratio = .502, p = .000), Non-Resident Alien (odds ratio = .326, p = .000) and Unknown (odds ratio = .788, p = .008) were less likely to perform in face-to-face courses compared to White students.
- Students who had a financial need in the fourth quartile (odds ratio = .799, p = .000) of $34,242 or greater were less likely to perform in face-to-face courses compared to the students with no financial needs.
- The higher a student's GPA prior to enrollment at the institution, the more likely the student was to perform in face-to-face courses (odds ratio = 3.206, p = .000)
- Students with higher SAT Verbal Scores (odds ratio = 1.001, p = .000) were more likely to perform in face-to-face courses.

- Students enrolled in the College of Engineering and Computer Science (odds ratio = 1.338, p = .001), the School of Management (odds ratio = 1.744, p = .000), and the School of Public Communications (odds ratio = 1.369, p = .010) were more likely to perform in a face-to-face course compared to students enrolled in the College of Arts and Sciences. However, students enrolled in the School of Architecture (odds ratio = .654, p = .002) were less likely to perform in a face-to-face course compared to students enrolled in the College of Arts and Sciences.

Models 5, 6, 7, and 8

This section presents the data and interpretation for the last four models (models 5 to 8), which include the independent variable CEP. As previously mentioned, this decision was made because, by using only the data set that included observations with CEP, the data set was greatly reduced. Since the researcher had access to the data, there was a value in the 9,439 observations, and therefore the four models were run again using the subset of data that included CEP as an independent variable.

Note that for the demographic variable race/ethnicity American Indian has been omitted, and so has the College of Continuing Education for the academic school/college variable in the online persistence and performance models. This is due to the fact that there were no students who had participated in a CEP opportunity that identified as American Indian or who had enrolled in the College of Continuing Education. The four models (see Table 36 below) that were executed were as follows:

1. The first model analyzed the student characteristics that predicted persistence in online courses,

2. The second model analyzed the student characteristics that predicted performance in online courses,
3. The third model analyzed the student characteristics that predicted persistence in face-to-face courses, and
4. The third model analyzed the student characteristics that predicted performance in face-to-face courses.

Table 36. Results for Models 5, 6, 7, and 8

	Model 5: Online Persistence with CEP		Model 6: Online Performance with CEP		Model 7: Face-to-Face Persistence with CEP		Model 8: Face-to-Face Performance with CEP	
	Coefficient (P>|z|)	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**
Demographics								
Male	-0.185 (0.673)	0.830	-0.400 (0.326)	0.670	-0.118 (0.279)	0.889	-0.497 (0.000)*	0.608
Age	0.543 (0.010)*	1.721	0.2778 (0.135)	1.320	-0.096 (0.009)*	0.909	0.075 (0.018)*	1.078
American Indian	(omitted)	(omitted)	(omitted)	(omitted)	-1.094 (0.015)*	0.335	-1.311 (0.006)*	0.270
Asian Pacific Islander	0.106 (0.907)	1.112	0.106 (0.908)	1.112	-0.384 (0.028)*	0.681	-0.378 (0.022)*	0.685
Black African American	-1.624 (0.070)	0.197	-2.225 (0.006)*	0.108	-0.221 (0.275)	0.082	-0.569 (0.002)*	0.566
Hispanic	-1.175 (0.100)	0.309	-1.012 (0.154)	0.364	-0.087 (0.656)	0.916	-0.317 (0.057)	0.728
Non-Hispanic/Multicultural	-3.041 (0.029)*	0.048	-3.218 (0.012)*	0.040	0.817 (0.187)	2.264	-0.166 (0.660)	0.847
Non-Resident Alien	-2.500 (0.010)*	0.082	-2.066 (0.032)*	0.127	-1.129 (0.000)*	0.323	-1.174 (0.000)*	0.309
Unknown	0.220 (0.820)	1.247	-0.296 (0.713)	0.744	-0.488 (0.007)*	0.614	-0.220 (0.227)	0.802
Financial Need								
need_q1 - 0 < $17,652	-1.209 (0.102)	0.299	-0.245 (0.739)	0.783	-0.273 (0.196)	0.761	-0.154 (0.419)	0.857
need_q2 - $17,652 ≤ $26,174	-0.844 (0.253)	0.430	-0.397 (0.565)	0.672	-0.417 (0.036)*	0.659	-0.176 (0.367)	0.838
need_q3 - $26,174 ≤ $34,242	-0.594 (0.484)	0.552	0.123 (0.879)	1.130	-0.350 (0.065)*	0.705	-0.217 (0.213)	0.805
need_q4 - $34,242 ≤ ∞	1.043 (0.140)	2.837	1.730 (0.010)*	5.642	-0.313 (0.022)*	0.731	-0.302 (0.013)	0.739
Academic Performance								
GPA Prior to Enrollment at Institution	0.771 (0.168)	2.162	0.122 (0.809)	1.129	0.901 (0.000)*	2.461	1.303 (0.000)*	3.679
SAT Math Score	-0.003 (0.469)	0.997	-0.000 (0.977)	1.000	-0.000 (0.592)	1.000	0.000 (0.565)	1.000
SAT Verbal Score	-0.000 (0.951)	1.000	-0.002 (0.492)	0.998	0.001 (0.345)	1.001	0.001 (0.105)	1.001
CEP	-0.002 (0.998)	0.998	0.729 (0.140)	2.073	0.201 (0.110)	1.223	0.239 (0.035)*	1.269

	Model 5: Online Persistence with CEP		Model 6: Online Performance with CEP		Model 7: Face-to-Face Persistence with CEP		Model 8: Face-to-Face Performance with CEP	
	Coefficient (P>|z|)	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**	**Coefficient (P>|z|)**	**Odds Ratio**
Academic School/College								
School of Education	-0.011 (0.994)	0.989	0.344 (0.795)	1.410	0.247 (0.349)	1.281	0.207 (0.360)	1.230
College of Engineering and Computer Science	1.213 (0.353)	3.363	0.329 (0.719)	1.389	0.088 (0.658)	1.092	0.187 (0.292)	1.205
College of Human Ecology	-1.101 (0.433)	0.332	-0.511 (0.715)	0.600	0.083 (0.776)	1.087	0.209 (0.415)	1.232
College of Sport and Human Dynamics	1.436 (0.275)	4.202	1.320 (0.212)	3.743	0.007 (0.977)	1.008	0.325 (0.178)	1.384
College of Visual and Performing Arts	-1.968 (0.003)*	0.140	-1.707 (0.003)*	0.181	-0.167 (0.276)	0.846	-0.001 (0.995)	0.999
School of Architecture	-4.327 (0.023)*	0.013	-3.874 (0.037)*	0.021	-1.295 (0.0000)*	0.274	-1.399 (0.000)*	0.247
School of Information Studies	-0.718 (0.356)	0.487	-0.113 (0.800)	0.893	-0.111 (0.580)	0.895	-0.394 (0.030)*	0.674
School of Management	0.4856 (0.512)	1.625	0.681 (0.305)	1.976	0.526 (0.009)*	1.692	0.838 (0.000)*	2.311
School of Public Communications	-0.191 (0.761)	0.826	0.191 (0.736)	1.211	0.190 (0.396)	1.209	0.068 (0.711)	1.070
College of Continuing Education	(omitted)	(omitted)	(omitted)	(omitted)	15.671 (0.998)	6396694.000	15.454 (0.995)	4149247.000
ln(L0)	-142		-171		-2105		-3428	
ln(LM)	-112		-138		-1940		-3101	
pseudo R^2	0.2113		0.1930		0.0784		0.0954	

* The p-value used to discern statistical significance was 0.05.
L0: likelihood of the model with no predictors, only the constant.
LM: likelihood of the estimated model.

MODELS 5 AND 6. The fifth model examined the student characteristics that predicted persistence in online courses, and the sixth model examined the student characteristics that predicted performance in online courses. Both models included the independent variable CEP. The definition for performance is the same as the one provided above. The researcher's hypotheses did not deviate from models 1 and 2, as previously stated.

For model 5, the pseudo R^2 value is 21.1%, which means that the model accounted for 21.1% of the variance. The results showed that:

- Students older in age were more likely to persist in online courses (odds ratio = 1.721, p = .010).

- Students who identified their race/ethnicity as Non-Hispanic/Multicultural (odds ratio = .048, p = .029) and Non-Resident Alien (odds ratio = .082, p = .010) were less likely to persist in online courses compared to White students.
- Students enrolled in the College of Visual and Performing Arts (odds ratio = .140. p = .003) and the School of Architecture (odds ratio = .013, p = .023) were less likely to persist in an online course compared to students enrolled in the College of Arts and Sciences.

For model 6, the pseudo R^2 value is 19.3%, which means that the model accounted for 19.3% of the variance. The results showed that:

- Students who identified their race/ethnicity as Black African American (odds ratio = .108, p = .006), Non-Hispanic/Multicultural (odds ratio = .040, p = .012), or Non-Resident Alien (odds ratio = .127, p = .032) were less likely to perform in online courses compared to White students.
- Students who had a financial need in the fourth quartile (odds ratio = 5.642, p = .010) of $34,242 or greater were more likely to perform in online courses compared to the students with no financial needs.
- Students enrolled in the College of Visual and Performing Arts (odds ratio = .181. p = .003) and the School of Architecture (odds ratio = .021, p = .037) were less likely to perform in an online course compared to students enrolled in the College of Arts and Sciences.

MODELS 7 AND 8. The seventh model examined the student characteristics that predicted persistence in face-to-face courses, the eighth model examined the student characteristics that predicted performance in face-to-face courses, and both models included the independent variable CEP. The definition for performance was unchanged. The researcher's hypotheses did not deviate from models 3 and 4, as stated above.

For model 7, the pseudo R^2 value is 7.8%, which means that the model accounted for 7.8% of the variance. The results showed that:

- Order students were less likely to persist in face-to-face courses (odds ratio = .909, p = .009).
- Students who identified their race/ethnicity as American Indian (odds ratio = .335, p = .015), Black African American (odds ratio = .681, p = .028), Non-Resident Alien (odds ratio = .323, p = .000), or Unknown (odds ratio = .614, p = .007) were less likely to persist in face-to-face courses compared to White students.
- Students who had a financial need in the second quartile (odds ratio = .659, p = .036), third quartile (odds ratio = .705, p = .065), and fourth quartile (odds ratio = .731, p = .022), were less likely to persist in face-to-face courses compared to the students with no financial needs.
- The higher a student's GPA prior to enrollment at the institution, the more likely the student was to persist in face-to-face courses (odds ratio = 2.461, p = .000)
- Students enrolled in the School of Management (odds ratio = 1.692, p = .009), were more likely to persist in a face-to-face course compared to students enrolled in the College of Arts and Sciences. However, students enrolled in the School of Architecture (odds ratio = .274, p = .000) were less likely to persist in a face-to-face course compared to students enrolled in the College of Arts and Sciences.

For model 8, the pseudo R^2 value is 9.5% which means, the model accounted for 9.5% of the variance. The results showed that:

- Gender may affect performance in face-to-face courses (male<female, odds ratio = .608, p = .000). In other words, Male students were less likely to perform compared to female students.
- Students older in age were more likely to perform in face-to-face courses (odds ratio = 1.078, p = .018).
- Students who identified their race/ethnicity as American Indian (odds ratio = .270, p = .006), Asian Pacific Islander (odds ratio = .685, p = .022), Black African American (odds ratio = .566, p = .002), and Non-Resident Alien (odds ratio = .309, p = .000), were less likely to perform in face-to-face courses compared to White students.
- The higher a student's GPA prior to enrollment at the institution, the more likely the student was to perform in face-to-face courses (odds ratio = 3.679, p = .000)
- If a student had participated in a CEP opportunity (odds ratio = 1.269, p = .035) prior to enrollment at the institution, that student was more to perform in a face-to-face course than those students who did not.
- Students enrolled in the School of Management (odds ratio = 2.311, p = .000), were more likely to perform in a face-to-face course compared to students enrolled in the College of Arts and Sciences. However, students enrolled in the School of Architecture (odds ratio = .247, p = .000) and the School of Information Studies (odds ratio = .674, p = .030) were less likely to perform in a face-to-face course compared to students enrolled in the College of Arts and Sciences.

Conclusion

For this study, the research questions were as follows:

1. Which undergraduate student characteristics best predict student success (persistence and performance) in online courses?
2. Which undergraduate student characteristics best predict student success (persistence and performance) in face-to-face courses?
3. Is there a difference between the characteristics of undergraduate students who successfully complete (persist) online courses and the characteristics of those whose performance is passing (perform)?
4. Is there a difference between the characteristics of undergraduate students who successfully complete face-to-face courses (persist) and the characteristics of those whose performance is passing (perform)?

In summary, the models run in this study elicited the following results (see Table 37 and Table 38 below):

Table 37. Summary of Results for all Eight Models

	Model 1 - Online Persist	Model 2 - Online Perform	Model 3 - F2F Persist	Model 4 - F2F Perform	Model 5 - Online Persist CEP	Model 6 - Online Perform CEP	Model 7 - F2F Persist CEP	Model 8 - F2F Perform CEP
Demographics								
Male			<Males - Less Likely to Persist>	<Males - Less Likely to Perform>				<Males - Less Likely to Perform>
Age			<Older - Less Likely to Persist>		**Older - More Likely to Persist**		<Older - Less Likely to Persist>	**Older - More Likely to Perform**
American Indian	<Less Likely to Persist>	<Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>			<Less Likely to Persist>	<Less Likely to Perform>
Asian Pacific Islander			<Less Likely to Persist>	<Less Likely to Perform>				<Less Likely to Perform>
Black African American		<Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>		<Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>
Hispanic	<Less Likely to Persist>		<Less Likely to Persist>	<Less Likely to Perform>				
Non-Hispanic/Multicultural	<Less Likely to Persist>	<Less Likely to Perform		<Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>		
Non-Resident Alien	<Less Likely to Persist>	Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>
Unknown			<Less Likely to Persist>	<Less Likely to Perform>			<Less Likely to Persist>	

*Not reporting percentages. The p-value used to discern statistical significance was 0.05.

	Model 1 - Online Persist	**Model 2 - Online Perform**	**Model 3 - F2F Persist**	**Model 4 - F2F Perform**	**Model 5 - Online Persist CEP**	**Model 6 - Online Perform CEP**	**Model 7 - F2F Persist CEP**	**Model 8 - F2F Perform CEP**
Financial Need								
need_q1 - 0 < $17,652								
need_q2 - $17,652 ≤ $26,174							<Less Likely to Persist>	
need_q3 - $26,174 ≤ $34,242							<Less Likely to Persist>	
need_q4 - $34,242 ≤ ∞			<Less Likely to Persist>	<Less Likely to Perform>		**More Likely to Perform**	<Less Likely to Persist>	
Academic Performance								
GPA Prior to Enrollment at Institution	**More Likely to Persist**	**More Likely to Perform**	**More Likely to Persist**	**More Likely to Perform**			**More Likely to Persist**	**More Likely to Perform**
SAT Math Score	<Higher Score - Less Likely to Persist>	<Higher Score - Less Likely to Persist>	<Higher Score - Less Likely to Persist>					
SAT Verbal Score			**Higher Score - More Likely to Persist**	**Higher Score - More Likely to Perform**				
CEP								**More Likely to Perform**

*Not reporting percentages. The p-value used to discern statistical significance was 0.05.

	Model 1 - Online Persist	Model 2 - Online Perform	Model 3 - F2F Persist	Model 4 - F2F Perform	Model 5 - Online Persist CEP	Model 6 - Online Perform CEP	Model 7 - F2F Persist CEP	Model 8 - F2F Perform CEP
Academic School/College								
School of Education								
College of Engineering and Computer Science	**More Likely to Persist**	**More Likely to Perform**	**More Likely to Persist**	**More Likely to Perform**				
College of Human Ecology								
College of Sport and Human Dynamics			**More Likely to Persist**					
College of Visual and Performing Arts		<Less Likely to Perform>	<Less Likely to Persist>		<Less Likely to Persist>	<Less Likely to Perform>		
School of Architecture			<Less Likely to Persist>	<Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>	<Less Likely to Persist>	<Less Likely to Perform>
School of Information Studies								<Less Likely to Perform>
School of Management	**More Likely to Persist**	**More Likely to Perform**	**More Likely to Persist**	**More Likely to Perform**			**More Likely to Persist**	**More Likely to Perform**
School of Public Communications	**More Likely to Persist**		**More Likely to Persist**	**More Likely to Perform**				
College of Continuing Education								

*Not reporting percentages. The p-value used to discern statistical significance was 0.05.

Table 38. Summary of Research Findings by Research Question

Research Question	Findings	Results Supported/Contradicted in Literature	Comments
R1: Which undergraduate student characteristics predict student success (persistence and performance) in online courses?	1. The higher the GPA prior to the enrollment at the institution the more likely the student is to succeed in online courses. 2. A student enrolled in the College of Engineering and Computer Science or the School of Management is more likely to succeed in online courses.	1. Consistent with literature. 2. Not depicted in literature.	1. Significant 2. New and significant
R2: Which undergraduate students characteristics predict student success (persistence and performance) in face-to-face courses?	1. The higher the GPA prior to the enrollment at the institution the more likely the student is to succeed in face-to-face courses. 2. The higher the score obtained on the SAT Verbal exam the more likely the student is to succeed in face-to-face courses. 3. A student enrolled in the College of Engineering and Computer Science, the School of Management, or the School of Public Communications is more likely to succeed in face-to-face courses. *CEP Data Set* 1. The higher the GPA prior to the enrollment at the institution the more likely the student is to succeed in face-to-face courses.	1. Consistent with literature. 2. Consistent with literature. 3. Not reported in literature. *CEP Data Set* 1. Consistent with literature.	1. Significant 2. Significant 3. New and significant *CEP Data Set* 1. Significant
R3: Is there a difference between the characteristics of undergraduate students who successfully complete online courses and the characteristics of those whose performance is passing?	1. Black African American students were less likely to perform in online courses. 2. Hispanic students were less likely to persist in online courses. 3. Students enrolled in the College of Visual and Performing Arts were less likely to perform in online courses. 4. Students enrolled in the School of Public Communications were more likely to persist in an online course. *CEP Data Set* 1. The older the student, the more likely he or she was to persist in online courses. 2. Black African American students were less likely to perform in online courses. 3. Students who qualified for financial need in quartile 4 were more likely to perform in online courses.	1. Consistent with literature. 2. Consistent with literature. 3. Not depicted in literature. 4. Not reported in literature. *CEP Data Set* 1. Not consistent with literature. 2. Consistent with literature. 3. Not reported in literature.	1. Significant 2. Significant 3. New and significant 4. New and significant *CEP Data Set* 1. New and significant 2. Significant 3. New and significant

*Reporting only statistically significant findings. The p-value used to discern statistical significance was 0.05.

Research Question	**Findings**	**Results Supported/Contradicted in Literature**	**Comments**
R4: Is there a difference between the characteristics of undergraduate students who successfully complete face-to-face courses and the characteristics of those whose performance is passing?	1. The older students became, the less likely they were to persist in face-to-face courses. 2. Students who identified as Non-Hispanic/Multicultural were less likely to perform in face-to-face courses. 3. Students who earned higher SAT Math Scores were less likely to persist in face-to-face courses. 4. Students enrolled in the College of Sport and Human Dynamics were more likely to persist in face-to-face courses. 5. Students enrolled in the College of Visual and Performing Arts were less likely to persist in face-to-face courses. *CEP Data Set* 1. Male students were less likely than female students to perform in face-to-face courses. 2. Students who identified as Asian Pacific Islander were less likely to perform in face-to-face courses. 3. Students who identified as Unknown were less likely to persist in face-to-face courses. 4. Students who qualified for need in quartiles 2, 3, and 4 were less likely to persist in face-to-face courses. 5. Students who had participated in a CEP prior to their enrollment at the institution were more likely to perform in face-to-face courses. 6. Students enrolled in the School of Information Studies were less likely to perform in face-to-face courses.	1. Not consistent with literature. 2. Consistent with literature. 3. Not consistent with literature. 4. Not depicted in literature. 5. Not depicted in literature. *CEP Data Set* 1. Consistent with literature. 2. Consistent with literature. 3. Not depicted in literature. 4. Not depicted in literature. 5. Not depicted in literature. 6. Not depicted in literature.	1. New and significant 2. Significant 3. New and significant 4. New and significant 5. New and significant *CEP Data Set* 1. Significant 2. Significant 3. New and significant 4. New and significant 5. New and significant 6. New and significant

*Reporting only statistically significant findings. The p-value used to discern statistical significance was 0.05.

There are many other possible variable combinations that could be attempted, but there are no guarantees that they would yield a model that is both theoretically valid and statistically robust. Though it was important to use the best and most rigorous tools available to answer the research questions, there are diminishing returns in departing far from theory and into a mathematical exercise of optimization. These techniques have been useful in helping to identify possible areas of concern and sources of misspecification. Now it is time, in Chapter 5, to return to the literature and theory in order to summarize what was learned and to make suggestions regarding future research.

CHAPTER 5: DISCUSSION

Online courses have proliferated over the last eight years (Christensen, Horn, Caldera, & Soares, 2011). In 2003 an estimated 10% of students took at least one online course, a statistic that grew to 30% in 2009 (Christensen et al., 2011). Results of a nationwide survey reveal that approximately four million students were enrolled in an online course in fall 2007 (Allen & Seaman, 2008). Face-to-face course offerings have increased at a rate of 1.2%, while online course offerings have increased at a 12.9% rate (Allen & Seaman, 2008). Despite the popularity of online education, course persistence and performance remain a problem faced by many colleges (Bowden, 2008; Kreideweis, 2005). This dissertation has examined which student characteristics predict student persistence and performance in online courses and the face-to-face equivalents at a private, four-year northeastern university.

To summarize, a multilevel model (MLM) design was selected and implemented for this research study. The data set had natural, nested groupings at more than one level. The academic school/college in which the student was enrolled was identified as level 2. The students enrolled (nested) within the academic school/college was identified as level 1. The model controlled for many available independent demographic and academic-performance variables. Findings from the study were presented in Chapter 4 along with general discussion of the MLM model. This chapter discusses the implications of these findings and concludes with a discussion of the implications for future research.

Discussion

PERSISTENCE. Previous studies had found that a variety of student characteristics predict student persistence and performance in online courses (Hart, 2012). Hart’s (2012) finding was upheld in this study, and a summary of the current study’s results by research question can be found in Table 38 above. In the present study, for students who had participated in an online course at a private four-year northeastern university, the multilevel model results indicate that students with higher GPAs prior to enrollment at the institution were more likely to succeed (persist and perform) in an online course, and that students enrolled in the College of Engineering and Computer Science or the School of Management were more like to succeed (persist and perform) in an online course.

In this study, for those students who had participated in a face-to-face equivalent course at a private four-year northeastern university, the multilevel model results indicate that students with higher GPAs prior to enrollment at the institution were more likely to succeed (persist and perform) in a face-to-face course; students that scored higher on the SAT Verbal exam had a higher likelihood to succeed (persist and perform) in a face-to-face course; and if the student was enrolled in the College of Engineering and Computer Science, the School of Management, or the School of Public Communications, he or she was more likely to succeed (persist and perform) in a face-to-face course. Additionally, for those students who had participated in a CEP prior to enrollment at the institution, the higher their GPA prior to enrollment at the institution, the more likely they were to succeed (persist and perform) in a face-to-face course.

GRADE POINT AVERAGE. The higher a student's GPA prior to enrollment, the more likely he or she was to persist in an online or face-to-face course equivalent. In fact, the literature reviewed often points to GPA as a predictor of student persistence and performance. Muse (2003); Dupin-Bryant (2004); Morris, Wu, and Finnegan (2005); Holder (2007); Aragon and Johnson (2008); and Harrell and Bower (2011) found that GPA was a critical factor that indicated which students were at risk for failing to successfully (persist) complete the web-based (online) course. This is consistent with the findings noted in Chapter 4 of this study. As shown above in Table 35, the higher a student's GPA prior to enrollment at the institution, the more likely he or she is to persist in online (odds ratio = 1.858, $p = .035$) and face-to-face (odds ratio = 2.317, $p = .000$) courses.

An unexpected finding in this study, however, was that GPA was not a predictor of persistence and performance in online courses for those students who had participated in a CEP prior to enrollment at the institution. However, GPA was a predictor of success for those students in face-to-face courses. One possible explanation for this finding that CEPs are structured and formatted like a face-to-face college campus course (Srinivas, 2012), so those students who participate in them prior to enrollment at a four-year institution will be better prepared to perform in a face-to-face course. Perhaps due to the structured nature of CEP courses, students who enroll in online courses after participating in a CEP are not prepared for the self-directed learning that is often required in an online course (Jaggers, 2014), as opposed to a face-to-face course where an instructor is there to guide student learning.

SAT EXAM SCORE. Lowenthal (2014) indicates that SAT scores were not a good predictor of student persistence or performance in online courses but does not indicate if SAT scores are a good predictor in face-to-face courses. This study found that the higher the score earned on the SAT verbal exam, the more likely the student was to persist and perform in face-to-face course equivalents. Further, this study found that students who achieved a higher score on the SAT math exam were less likely to persist in online courses, and to persist and perform in the face-to-face equivalents. In contrast, Morris, Wu, and Finnegan (2005) conclude that SAT math score was an important predictor of persistence in fully online courses, which does not match the results in this study. Morris et al. (2005) also found that "there was a significant and positive relationship between SAT math and verbal scores" (p. 29). The results with regard to SAT math exam scores are surprising.

According to the National Center for Fair and Open Testing (2007), the SAT exam is "designed to predict first-year college grades," and "it is not validated to predict grades beyond the freshman year or graduation rates." The data set used for this study did not include class standing (freshman, sophomore, junior, senior) as the researcher was interested in all undergraduates that had participated in an online course or a face-to-face equivalent. However, an educated guess can be made about the population included in this data set based on a field in the data set. The field, "total_taken_cum_GPA" totals the number of credit hours the student has completed (not including students who dropped out of courses), which helps with the calculation of the overall GPA for the student. To be considered a full-time undergraduate student, a student must take a minimum of 12 credits each semester, resulting in a total of 24 credits for an academic year. Assuming any student with 24 credits or less was considered a freshman, this data set contained 37,400 students out of 42,280 (88.5%) that had participated in more than 25 credits and would be considered a sophomore, junior, or senior. If this is true, it may explain why this study found students who achieved a higher score on the SAT math exam were less likely to persist in online courses and less likely to persist and perform in the face-to-face equivalents.

ACADEMIC SCHOOL/COLLEGE. According to a report conducted by the National Science Foundation and titled, *Science and Engineering Indicators 2012*, science and engineering students persist and complete undergraduate programs at a higher rate than nonscience and engineering students. Six years after enrollment in a four-year college or university in the 2003–2004 academic year, 63% of science and engineering students had completed a bachelor's degree by spring 2009, compared to 55% of nonscience and engineering students (National Science Foundation, 2012). The presentation of facts about science and engineering students could be used to corroborate the results of the present study, which found that students enrolled in the College of Engineering and Computer Science were more likely to succeed (persist and perform) in online courses and the face-to-face equivalents. This study also found that students enrolled in the School of Management were more likely to succeed (persist and perform) in online courses and the face-to-face equivalents. An article published in *Forbes Magazine* (Skorton & Altschuler, 2012) states that individuals with "engineering degrees experience lower unemployment and make more money than graduates in any other major." The article goes on to say that other undergraduate majors, including business, are next in line to engineering.

This study found that students enrolled in the School of Public Communications were more likely to succeed (persist and perform) in face-to-face courses, and this may be the result of unobserved heterogeneity. The data set for this study only had 2,248 (5.51%) students enrolled in the School of Public Communications and in a face-to-face course, which is small in comparison to the overall population enrolled in face-to-face courses (n = 40,798).

PERFORMANCE. As previously stated and supported by the literature, students are less likely to complete an online course than a traditional face-to-face course. Students are also "less likely to complete an online course with a passing grade" (PPIC, 2014). Examined in this study was whether or not there was a difference between the characteristics of undergraduate students who successfully completed online courses or a face-to-face equivalent and the characteristics of those whose performance was passing. Passing performance was defined as successfully completing an online or face-to-face course with a grade of C or better for undergraduate students (Ball State University, 2014).

GENDER. For those students who had participated in a CEP course prior to enrollment at the institution, the multilevel model highlighted that male students were less likely than female students to perform in face-to-face courses, but this finding was not indicated for persistence in face-to-face courses. This finding is not surprising and is substantiated in the literature. Females not only enter college at higher rates than males, but they are less likely to drop out (Dwyer, Hodson, & McCloud, 2013); however, no explanation for this finding emerged in this study. This study did not examine course design, but the implications of course design would be a valuable focus for a future research study. Female graduates now account for about 60% the United States bachelor's degree holders (Dwyer et al., 2013). At the institution under study, the percentage of full-time, first-time students who began their studies in fall 2008 and received a degree within six years was 81% for females and 79% for males (National Center for Education Statistics, 2015).

AGE. The multilevel model did highlight differences between the characteristics of undergraduate students who successfully completed face-to-face courses and whose performance was passing. For example, as students age, they are less likely to persist in face-to-face courses. This was not surprising, but it was surprising that this was not the case for performance in face-to-face courses. One could assume that, as a student matures and ages, he or she is more likely to perform well in his or her courses, regardless of delivery format. The number of students between the ages of 25 and 46 in this data set was n = 166 (overall n = 42,280), which may have contributed to this finding.

For those students who had participated in a CEP course prior to enrollment at the institution, the multilevel model did highlight that, as students aged, they were more likely to persist in online courses, but this finding was not indicated for performance in online courses. This finding differed from the finding previously discussed for face-to-face courses, which indicated that older students were less likely to persist in face-to-face courses. This finding is not surprising in that online course offerings are flexible and can be taken anytime and anywhere. This flexibility is well suited for older students who may be working and juggling a family.

RACE/ETHNICITY. The multilevel model did highlight differences between the characteristics of undergraduate students who successfully completed online courses and the characteristics of those whose performance was passing. For example, Black African American students were less likely to perform in online courses, but no statistically significant finding was indicated for student persistence. This same finding was found for those students who had participated in CEP courses prior to enrollment at the institution. In the state of California, African Americans are among a group of identified students that are likely to perform worse in online courses than in traditional ones (PICC, 2014). A similar result was found in the present study for students who identified as Non-Hispanic/Multicultural in face-to-face courses.

Hispanic students in this study, on the other hand, were less likely to persist in online courses, but no statistically significant finding was indicated with regard to student performance. Carter (2006) states that racial or ethnic minority students have a higher probability of leaving nonsecondary education than ethnic majority groups, which supports this study’s finding that Hispanic students were less likely to persist in online courses. Both of these populations, Black African American and Hispanic, were small samples (total n = 225) within the data set, with n = 130 Black African American students that did not drop an online course and n = 95 Hispanic students that did not drop an online course out of a total of n = 1,271 students who did not drop an online course. The results of this study should be substantiated with a larger population in future studies.

Additional resources should be provided to minority students to help them develop the academic skills necessary to perform well in their courses. Those resources should include orientation to acclimate them to the online environment, online tutorials, or help desks that these students can utilize when they begin to experience difficulties in the online environment. In addition to academic support, a student success course designed for students who wish to enroll in an online course could be offered. This course could be designed to expose students to the types of study habits that can increase academic success. The course could present students with information about time management, study skills, and test-taking strategies while preparing them for the online experience before they enroll in an online course.

Those students who had participated in a CEP course prior to enrollment at the institution and identified as Asian Pacific Islander were less likely to perform in face-to-face courses, but no statistically significant finding was indicated for persistence in face-to-face courses. The total number of Asian Pacific Islander students enrolled in a face-to-face course was n = 3,803 out of n = 40,798 total students enrolled in a face-to-face course. Asian Pacific Islanders enrolled in face-to-face courses accounted for only 9.32% of the population in this data set. This result could be attributed to the small size of the sample within the overall data set, and therefore the results of this study should be substantiated with a larger population in future studies. Therefore, the results of this study must be interpreted with caution due to the lack of a large sample size for this race/ethnicity.

Additionally, students who had participated in a CEP course prior to enrollment at the institution and who identified as Unknown were less likely to persist in face-to-face courses, but this finding was not indicated for performance in face-to-face courses. Again, in this data set the total numbers for Asian Pacific Islander (n = 869, 9.57%) and Unknown (n = 652, 7.18%) were small compared to the overall total, n = 9,082.

As dipicted in Table 10 in chapter four of this study, minority students do dropout of courses more than the reference group which was White students. The data suggests there is further research that can be done with regard to minority students by conducting a post-hoc analysis. A post-hoc analysis could reveal a general trend about a particular minority group or may call for different groupings of minority groups to better understand a general trend that may emerge.

By replicating this study and adding a qualitative component, a researcher may be able to identify why minoritiy students dropout of courses, regardless of delivery format. Could the reason for dropout be related to cultural or race/ethnicity factors, motivational factors, appropriate academic student support services or a lack of exposure and understanding of a particular course format. A future study focusing on minority students would be important, and as Carter (2006) points out, it is a "necessity to understand retention issues, especially for underrepresented students" (p. 34).

SAT EXAM SCORE. This study indicated that those students who earned a higher SAT math score were less likely to persist in face-to-face courses, but this finding was not indicated for their performance in face-to-face courses. This finding was previously reported and discussed above with regard to persistence. Logically, it would seem that the better students performed on a standardized exam, the more likely they would be to perform in college level courses, but that is not supported by this finding. As previously discussed, the SAT exam is designed to predict the grades students may achieve in their freshman year (National Center for Fair and Open Testing, 2007), but not beyond. Reports in mainstream media argue that good testing does not promise college success (Paulos, 2015; Sheffer, 2014). This study did not examine insights into the pedagogical design of courses, techniques for the administration of academic programs, or the execution of courses regardless of the delivery format (online or face-to-face). All of these factors could be possible reasons why students who earned a higher SAT math score were less likely to persist in a face-to-face courses.

ACADEMIC SCHOOL/COLLEGE. Additionally, students enrolled in the College of Visual and Performing Arts were less likely to perform in online courses, but no statistcally significant findings were indicated for those students and their persistence in online courses. In contrast, students enrolled in the School of Public Communications were more likely to persist in an online course, but no statistically significant finding was indicated as to whether they would be more likely to perform in the online course. Additionally, for a face-to-face course, students enrolled in the School of Public Communications were more likely to persist and perform. In contrast, students enrolled in the College of Sport and Human Dynamics were more likely to persist in face-to-face courses, but this finding was not indicated for performance in face-to-face courses.

Both of the previously described results about the School of Public Communications and the College of Sport and Human Dynamics may be due to unobserved heterogeneity. That is, there is variation across the individual units of observations (academic school/college), and since this variation (heterogeneity) cannot be observed as it relates to the dependent variable (persistence or performance), the result is unobserved heterogeneity.

The School of Visual and Performing Arts had 11.76% of students enrolled in online courses (n = 42 and n = 29 did not drop an online course); for the School of Public Communications 19.05% of students were enrolled in an online course (n = 68 and n = 60 did not drop an online course); and for the College of Sport and Human Dynamics 6.16% were enrolled in an online course (n = 22 and n = 5 did not drop an online course). These numbers, in comparison to the overall data (n = 42,280) set are not large.

Those students who had participated in a CEP course prior to enrollment at the institution and who had enrolled in the School of Information Studies were less likely to perform in face-to-face courses, but this finding was not indicated for persistence in face-to-face courses. This result may also be due to unobserved heterogeneity.

FINANCIAL AID. Regarding students who had participated in a CEP course prior to enrollment at the institution, the multilevel model did highlight that those students who qualified for financial need in quartile 4 were more likely to perform in online courses, but no statistically significant finding was indicated for persistence in online courses. Similarly, students who qualified for financial need in quartiles 2 or 4 were more likely to perform in face-to-face courses, but no statistically significant findings were indicated for persistence in face-to-face courses. These results may be due to unobserved heterogeneity. The total number of students who qualified for quartile 4 was 3,624 (38.39%), with 240 (38.90%) dropping out of courses, regardless of delivery format. For quartile 2 the total number of students who qualified was 759 (8.04%), with 56 (9.08%) dropping out of courses, regardless of delivery format.

Strengths of Study

The strengths of the study are as follows:

- The nature of this rich data set allowed for the control of demographic and academic performance variables.
- Use of control variables in MLM strengthened the internal validity of research findings of the identified predictor variables.

- Previous studies have examined course attrition in both online and face-to-face equivalents, but this study also examined performance.

Limitations of Study

The limitations of this study are as follows:

- This study did not account for the difference in data on the types of instructional strategies (e.g., scaffolding, level of participation, and requirements for courses) used and not used within the courses that were being investigated. These have been shown in the literature to be important predictors of persistent and performance in online courses and the face-to-face equivalents.
- The data set did not include data on student learning and educational preferences.
- This study did not address the issue of *why* students drop out of or persist in online courses.
- This study did not examine course delivery modes such as blended or hybrid courses.
- Internal validity seeks to establish a causal relationship between two variables, but this study engaged in ex-post facto research. The independent variables could not be manipulated and therefore no causal relationships could be identified.
- This study was based on a single institution; hence the results are not generalizable.

Conclusion

This study investigated the student characteristics (gender, age, race/ethnicity, financial need, GPA prior to enrollment at the institution, SAT scores, and CEP) that predict student persistence and performance in online courses and the face-to-face equivalents. The results of this study demonstrate the student characteristics that predict student success (persistence and performance) in online courses and the face-to-face equivalents—as well as the complexity of this topic and the need for future research to offer conclusive and definitive results.

Using the revised model presented in Figure 3, in chapter 1, institutions can replicate and implement this study to inform student persistence and performance in both online and face-to-face courses at their respective institutions. This should be done at a wide variety of institutions, both public and private, consisting of different sizes and student populations.

While many of the results of the current study did substantiate results already reported in the literature of this field, many new statistically significant findings emerged. Through the use of this data set, it was found that students enrolled in the College of Engineering and Computer Science or the School of Management were more likely to succeed in online and face-to-face courses, which is a new contribution to the field. Another contribution is the finding that students enrolled in the College of Visual and Performing Arts were less likely to perform in online courses, and that students enrolled in the School of Public Communications were more likely to persist in online courses. Finally, with regard to those students who had participated in a CEP prior to enrollment at the institution, new findings were that, as a student aged, he or she was more likely to persist in an online course, and that those students who qualified for financial need in quartile 4 were more likely to perform in online courses.

Researchers should replicate this study across multiple institutions, focusing specifically on college of engineering and computer science and school of management to further validate the results of this study. A qualitative component should be included with this study to find out why these students are more likely to succeed in online courses and the face-to-face equivalents. This information could then be used by administrators to improve student support services, advisement, and course design.

Aligning with much of the literature in this area, the results of this study demonstrate consistently that GPA prior to enrollment at the institution predicts student success in both online courses and the face-to-face equivalents. Therefore, from an instructional design perspective, students with low GPAs should be provided with instructional resources to help them develop academic skills necessary to perfrom well in their courses and be better supported to persist in completing courses. New instructional resources might include a video- or animation-based orientation that acclimates students to the college classroom environment (both online and face-to-face), and perhaps a set of short tutorials that support student needs to develop good study and time management skills and set learning goals. Design ideas may also include developing different types of opportunities prompting students to interact with instructors in real time or through virtual methods, asynchronously. These types of resources and activities may help student develop better (and easier) strategies to get needed assistance, reduce their fear to ask for help, and allow them multiple ways to get the assistance they need, rather than drop out or do poorly. It might also be valuable to design short video with students from different backgrounds who previously completed courses successfully sharing their thoughts on relevance of content, study and time management strategies, and pitfalls to watch out for to avoid falling behind, getting lost, or doing poorly.

Consistently, those students who identified their race/ethnicity as a minority were less likely to succeed in online courses and the face-to-face equivalents. This result was consistent even for those students who had participated in a CEP prior to enrollment at the institution. This study should be replicated with multiple institutions. Valuable information could be obtained by determining whether the outcomes would be similar in other institutions. Such a study would provide data to support administrators' investment in student support services for both students enrolled in online courses and face-to-face courses such as; study habit strategies and techniques to improve students' study skills, technology use support, and/or motiviational prompts that align with cultural charactiersitcs.

This study's results confirm that, after controlling for all available student characteristics, persistence and performance are complex issues and it is not creditable to attribute student success (persistence and performance) to any single student characteristic (Rovai, 2004; Hart, 2012). In initiating a learner analysis, an important task for an instructional designer is to identify those characteristics most critical to the achievement of the training objectives. This study examined general learner characteristics such as age, gender, race/ethnicity, socioeconomic status, GPA, CEP, and SAT scores. However, individual characteristics of learners (age, gender, race/ethnicity, socioeconomic status, GPA, CEP, and SAT scores) cannot easily predict the success (persistence or performance) or lack of success in an online or face-to-face course, as the results of the current study indicate.

Instructional designers must look beyond the individual student characteristics, which account for a small measure of persistence and performance, and focus on course design pedagogies that engage learners with varying characteristics, or identifying and measuring the characteristics of those students who perform and persist in online courses and face-to-face courses. It is important to emphasize that the current study was not a comparison study. Future researchers should be aware of the pitfalls of comparing online and face-to-face courses because the instructional design implications for these individual course delivery modes differ.

The instructional design differences between the two delivery modes and even between courses in the same delivery mode (variation between online courses and variation between face-to-face courses) could account for some of the variance in the results of the current study.

Therefore, more research should be centered on design theory that relates to success (persistence and performance) in undergraduate courses and how these courses are designed. Some literature in online instruction points to how design can be related to attrition and level of engagement, which can often relate to student performance. Additionally, other student characteristics such as time management and communication skills have been shown in previous research to be related to success in online instruction. Another avenue for future research would be to examine students' perceptions of models of instruction, such as teacher, cognitive, or social presence, and how each relates to student success (persistence and performance).

Utilizing the results of this study, a future researcher might consider additional analysis of the statistically significant variables by examining various combinations of variables more closely to see if they can better predict student success (persistence and performance) or not.

Since this study followed only students enrolled in online courses and the face-to-face equivalents at a single four-year private northeastern university, it would be interesting to find out what student characteristics predict student success (persistence and performance) in online courses and the face-to-face equivalents across many institutions, public and private. Future research could specifically focus on online course offerings alone in the hopes of increasing the final data population. The modifications to the Kember model, previously presented in Chapter 1 (see Figure 3), in this study will be beneficial to this type of replication study.

The modified version of Kember's model depicted in Figure 3 in Chapter 1 of this study focused on Kember's (1995) student entry characteristics which were highlighted in Kember's model as an important facet of his model. The modifications to Kember's model for this study are an acute focus on the student entry characteristics.

The student entry characteristics, included in the modified model for this study, were grouped into two categories; by demographics (age, gender, race/ethnicity, and socioeconomic status) and by academic performance (GPA prior to enrollment to the institution, verbal and math SAT scores and CEP) for the undergraduate student. These undergraduate student entry characteristics stay with the student as the student enrolls in either an online course or a face-to-face course. Course persistence and then course perfomrance or lack of course persistence and then course dropout may or may not be predicted by the undergraduate student entry characteristics.

These modifications were made because student entry characteristics are an important aspect of instructional deisgn (Smith & Regan, 2005). Instructional designers must consider the characteristics of the learner in order to inform the section of instructional strategies which will be used to produce effective course instruction and meaningful learning activites and experiences for the learner. Kember's model focused on not only the student entry characteristics but also on external, social and academic components that may affect a student's progress in an online course.

The intense focus on the undergraduate student entry characteristics for this study, was important because this study's results confirm that, after controlling for all available student characteristics, student persistence and performance are complex issues. Student success (persistence and performance) cannot be attributed to any single student characteristic. Instructional designers must identify the combination of student characteristics most critical to the achievement of the intended learning outcome. This is important to keep in mind as future researchers replicate this study and produce useful results in a complicated area of study (student persistence and performance).

Given the long-term personal and socioeconomic benefits of attaining a college degree (Johnson, 2012), this study may help higher education administrators, faculty, and staff gain a better understanding of student variables that affect their persistence and performance in courses, regardless of delivery format. These results suggest opportunities for additional studies that explore and unpack the relationships among student support services and student persistence and performance. Finally, these results give insights into instructional enhancments that can help all students become better prepared to be successful in their studies, in classrooms or online environments.

APPENDIX A

GLOSSARY OF TERMS

The following definitions were each from Ball State University (Ball State University, 2014).

Course Attrition: loss of students in a course, which could have either an online or face-to-face format.

Face-to-Face Course: a course taught synchronously, with students and instructors physically present, in a physical campus location.

Online Course: a course taught asynchronously and delivered/accessed online, primarily without scheduled class sessions or real-time interaction and with students and instructors physically separated.

Performance: completion of an online or face-to-face course with a grade of C or better for undergraduate students.

Student Success: demonstration of persistence and performance that meet the criteria outlined by the university (Ball State University, 2014).

APPENDIX B

INDEPENDENT VARIABLE LIST

Variable	Definition of Variable
Unique_ID	Unique identifier of student
Female	Indicator for female 1 = female; 0 = otherwise
Male	Indicator for male 1 = male; 0 = otherwise
GenderUnkown	Indicator for unknown gender 1 = unknown; 0 = otherwise
AmIndian	Indicator for American Indian 1 = American Indian; 0 = otherwise
AsianPI	Indicator for Asian/Pacific Islander 1 = Asian Pacific Islander; 0 = otherwise
BlackAfAmer	Indicator for Black/African American 1 = Black/African American; 0 = otherwise
Hispanic	Indicator for Hispanic 1 = Hispanic; 0 = otherwise
NonHispanicMulti	Indicator for non-Hispanic/more than one race/ethnicity 1 = non-Hispanic/multi-race/ethnicity; 0 = otherwise
NonResAlien	Indicator for nonresident alian 1 = nonresident Alian; 0 = otherwise
RaceEthUnkown	Indicator for race/ethnicity unknown 1 = race/ethnicity unknown; 0 = otherwise
White	Indicator for White 1 = White; 0 = otherwise
Course_Dropped	Indicator for if student dropped course 1 = yes course dropped; 0 = no course not dropped
Instructional_Mode_Physical	Indicator for course with instructional mode of physical 1 = physical; 0 = otherwise
Instructional_Mode_Online_Synchronous_NonResidency	Indicator for course with instructional mode of online synchronous nonresidency 1 = online synchronous nonresidency; 0 = otherwise
GPAbeforeSUundergrad	GPA earned prior to enrollment at Syracuse University on a 4-point scale 0-4
Curr_Age	Age of student 18 to 48
SAT_Math_Score	SAT Math score zero to 800
SAT_Verb_Score	SAT Verbal score zero to 800
Need_NoFAFSA	Indicator for FAFSA did not file 1 = FAFSA not filed; 0 = otherwise
Need_Zero	1 = FAFSA form filed but zero dollar need; 0= otherwise
Need_Q1	1 = FAFSA from filed and first quartile dollar need; 0 = otherwise
Need_Q2	1 = FAFSA from filed and second quartile dollar need; 0 = otherwise

Variable	Definition of Variable
Need_Q3	1 = FAFSA from filed and third quartile dollar need; 0 = otherwise
Need_Q4	1 = FAFSA from filed and fourth quartile dollar need; 0 = otherwise
APandSImilarCredit_Participated_In	Indicator for if the student had participated in a CEP 1 = yes participated in a CEP; 0 = no participation in a CEP

SYRACUSE UNIVERSITY
Office of Research Integrity and Protections
MEMORANDUM

TO:	Kalpana Srinivas
DATE:	November 12, 2013
SUBJECT:	**IRB Review Not Required**
IRB #:	13-318
TITLE:	*Data Analysis of Online Courses Offered Through University College at Syracuse University and Corresponding Face-To-Face Courses to Find the Effect of These Courses on Both Student Persistence and Performance*

It has been determined by the Office of Research Integrity and Protections that the information submitted pertaining to the above referenced protocol does not meet the definition of human subjects research ("a systematic investigation, including research development, testing and evaluation, designed to develop or contribute to generalizable knowledge involving any intervention or interaction with a living individual about whom an investigator conducting research obtains data through an intervention or interaction, or identifiable private information.") and does not require IRB oversight.

Should there be any change in the nature of the activity originally proposed (e.g. testing results used for research purposes), a new protocol application specific to these changes must be submitted. Thank you for your cooperation in our shared efforts to assure that the rights and welfare of people participating in research are protected.

Sincerely,

Tracy Cromp, Director
Office of Research Integrity and Protections

Note to Faculty Advisor: *This notice is mailed to faculty. If a student is conducting this study, please forward this information.*
DEPT: Chancellor's Office, Crouse Hinds Hall, Suite 600 **STUDENT:** Karen Bull

Office of Research Integrity and Protections
121 Bowne Hall ♦ Syracuse, New York 13244-1200
(Phone) 315.443.3013 ♦ (Fax) 315.443.9889
orip@syr.edu ♦ www.orip.syr.edu

References

Allen, I. E., & Seaman, J. (2007). *Online nation: Five years of growth in online learning.* Needham, MA: Sloan-C.Allen, I. E., & Seaman, J. (2008). *Staying the course: Online education in the United States.* Needham, MA: Sloan-C.

Allen, I. E., & Seaman, J. (2011). *Going the distance: Online education in the United States, 2011*. Needham, MA: Sloan-C.

Allen, I. E., & Seaman, J. (2013). *Changing course: Ten years of tracking online education in the United States.* Needham, MA: Sloan-C.

Allen, I. E., & Seaman, J. (2014). *Grad Change: Tracking online education in the United States.* Needham, MA: Sloan-C.

American College Testing. (2012). *National collegiate course attrition and persistence to degree rates* (Report No. 6195). Retrieved from https://www.noellevitz.com/documents/shared/Papers_and_Research/2012/2012-ACT Course attrition -Data.pdf.

Anderson, T. (2004). Student services in a networked world. In J. Brindley, C. Walti, & O. Zawacki-Richter (Eds.), *Learner support in open, distance and online learning environments*. Oldenburg, Germany: Bibliotheks-und Informationsystem der Universität Oldenburg.

Aragon, S. R., & Johnson, E. S. (2008). Factors influencing completion and noncompletion of community college online courses. *The American Journal of Distance Education*, *22*(3), 146–158.

Babbie, E. (1998). *Survey research methods* (2nd ed.). Belmont, CA: Wadsworth Pub. Ball State University. (Registrar) http://cms.bsu.edu/-/media/WWW/

DepartmentalContent/AcademicSystems/Banner%20User%20Guides/Coding%20Syste %20for%20Courses%20%20Schedule%20Builders.pdf

Ball State University. Registration and Academic Progress. (2015, September 10). Retrieved from http://cms.bsu.edu/about/administrativeoffices/registrar.

Boston, W., Ice, P. and Gibson, A. (2011). Comprehensive assessment of student retention in online learning environments. *Online Journal of Distance Learning Administration*. Retrieved from http://www.westga.edu/~distance/ojdla/spring141/boston_ice_gibson141.html

Bowden, J. (2008). Why do nursing students who consider leaving stay on their courses? *Nurse Researcher*, *15*(3), 45–59.

Bower, B. (2001). Distance education: Facing the faculty challenge. *Online Journal of Distance Learning Administration*, *4*(2). Retrieved from http://www.westga.edu/ ~distance/ojdla/summer42/bower42.html

Bunn, J. (2004). Student persistence in a LIS distance education program. *Australian Academic Research Libraries*, *35*(3), 253–270.

Carlson, S. (2013, October 15). Traditional Education Beats Online in Key Areas Opinion Poll Finds Comments. Retrieved September 10, 2015.

Carr, S. (2000). As distance education comes of age, the challenge is keeping the students. *The Chronicle of Higher Education*, *46*(23), A39–A41.

Carter, D. F. (2006). Key issues in the persistence of underrepresented minority students. *New Directions for Institutional Research 2006* (130), 33–46. Retrieved from http://deepblue.lib.umich.edu/bitstream/handle/2027.42/49309/178_ftp.pdf?sequence=1.

Christensen, C. M., Horn, M. B., Caldera, L., & Soares, L. (2011). Disrupting college: How disruptive innovation can deliver quality and affordability to postsecondary education. Retrieved from The Center for American Progress website: https://www. americanprogress.org/issues/labor/report/2011/02/08/9034/disrupting-college/

Clark, R. E. (1983). Reconsidering research on learning from media. *Review of educational research*, 53(4), 445-459.

Clark, R. E. (1994). Media will never influence learning. *Educational technology research and development*, *42*(2), 21-29.

Cochran, J. D., Campbell, S. M., Baker, H. M., & Leeds, E. M. (2013). The role of student characteristics in predicting retention in online courses. *Research in Higher Education*, 1–22.

Cole, R. A. (2000). *Issues in Web-based pedagogy: A critical primer*. Westport, CT: Greenwood Press.

Diaz, D. P., & Bontenbal, K. F. (2001). Learner preferences: Developing a learner-centered environment in the online or mediated classroom. *Ed at a Distance*, *12*(8).

DiBiase, D. (2000). Is distance teaching more work or less work? *The American Journal of Distance Education*, *14*(3), 6–20.

Dillon, K., Dworkin, J., Gengler, C., & Olson, K. (2008). Online or face to face? A comparison of two methods of training professionals. *Journal of Family and Consumer Sciences*, *100*(3), 28–33.

Dervarics, C. (2009, April 16). Obama agenda focuses on degree completion. *Diverse Issues in Higher Education*. Retrieved from http://diverseeducation.com/ article/12435/.

Dunagan, S. P. (2005). Performance and attrition rates of students in online versus face-to-face physical geology courses. In *Proceedings of the Geological Society of America* [Abstracts with programs], *37*(7), 408.

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

Dwyer, R. E., Hodson, R., & McCloud, L. (2013). Gender, debt, and dropping out of college. *Gender & Society, 27*(1), 30–55.

EDUCAUSE. (2013). 7 things you should know about MOOCs. EDUCAUSE Learning Initiative. Retrieved from http://net.educause.edu/ir/library/pdf/ELI7097.pdf.

EdTech Times Staff (2012). *The evolution of distance learning in higher education*. Retrieved from http://www.evolution-of-distance-learning.com/.

Fike, D. S., and R. Fike. 2008. Predictors of first-year student retention in the community college. *Community College Review, 36*(2): 68–88.

Finnegan, C. (2005). Predicting retention in online general education courses. *American Journal of Distance Education, 19*(1), 23–36.

Frankola, K. (2001). Why online learners drop out. *Workforce, 80*(10), 53–58.

Flowers, L., White, E., & Raynor, J. E. (2012). Examining the transactional distance theory in a web-enhanced biology course. *Journal of Studies in Education, 2*(3), 144–154.

Gallup. (2013, October). *In U.S., online education rated best for value and options: Viewed as weakest in terms of trusted grading and acceptance by employers.* Retrieved from http://www.gallup.com/poll/165425/online-education-rated-best-value-options.aspx.

Gannon-Cook, R., & Sutton, R. (2012, June). Hard lessons learned: Administrators' assessments of online courses and student retention. In *World Conference on Educational Multimedia, Hypermedia and Telecommunications, 2012*(1), 818–826.

Garson, G. D. (2013). Fundamentals of hierarchical linear and multilevel modeling. In *Hierarchical linear modeling: Guide and applications* (pp. 3–25). Thousand Oaks, CA: Sage Publications,

Gibson, C. C. (1996). Toward an understanding of academic self-concept in distance education. *The American Journal of Distance Education, 10*(1), 23–36.

Goldstein, H. (2011). *Multilevel statistical models* (4th ed.). University of Bristol, UK.

Harrell, I. L., & Bower, B. L. (2011). Student characteristics that predict persistence in community college online courses. *American Journal of Distance Education, 25*(3), 178-91.

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.

Hastings, N. B., & Tracey, M. W. (2004). Does media affect learning: Where are we now? *Tech Trends*, 49(2), 28–30.

Holder, B. (2007). An investigation of hope, academics, environment, and motivation as predictors of persistence in higher education online programs. *Internet & Higher Education*, *10*(4), 245–260.

Infographic History of Distance Education (History of Distance & Online Education Infographic) http://www.straighterline.com/online-education-resources/online-education tools/infographic-history-of-distance-education/.

Jaggars, S. S. (2014). Choosing between online and face-to-face courses: Community college student voices. *American Journal of Distance Education*, *28*(1), 27–38.

Johnson, N. (2012). *The institutional costs of student attrition*. Retrieved from http://www.deltacostproject.org/resources/pdf/Delta-Cost-Attrition-Research-Paper.pdf.

Kember, D. (1995). *Open learning courses for adults: A model of student progress*. Englewood Cliffs, NJ: Educational Technology Pub.

Kemp, W. C. (2002). Persistence of adult learners in distance education. *The American Journal of Distance Education*, *16*(2), 65–81.

Kozma, R. (1991). Learning with media. *Review of Educational Research*, *61*(2), 179–211.

Kozma, R. (1994). Will media influence learning: Reframing the debate. *Educational Technology Research and Development*, *42*(2), 7–19.

Kreideweis, J. (2005). Indicators of success in distance education. *CIN: Computers, Informatics, Nursing*, *23*(2), 68–2.

Leech, N., Barrett, K., & Morgan, G. (2011). *IBM SPSS for introductory statistics: Use and interpretation* (5th ed.). New York: Routledge.

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

Lim, C. K. (2001). Computer self-efficacy, academic self-concept, and other predictors of satisfaction and future participation of adult distance learners. *The American Journal of Distance Education*, *15*(2), 41–51.

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.

Lowenthal, P. (June 10, 2014). Improving student retention in online learning. *Academic Partnerships*. Lecture conducted from Boise State University, Boise, ID.

Lynch, M. (2001). Effective student preparation for online learning. Retrieved from The Technology Source Archives at the University of North Carolina: http://technologysource.org/article/ effective_student_preparation_for_online_learning/

Mathes, J. L. (2003). Predictors for student success in online education (Doctoral dissertation, University of Illinois, Urbana), .

Mayes, R., Luebeck, J., Ku, H. Y., Akarasriworn, C., & Korkmaz, Ö. (2011). Themes and strategies for transformative online instruction: A review of literature and practice. *Quarterly Review of Distance Education*, *12*(3), 151.

Means, B., Toyama, Y., Murphy, R., Bakia, M., & Jones, K. (2010). Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies. Retrieved from the U.S. Department of Education Office of Planning, Evaluation, and Policy Development Policy and Program Studies Service website: https://www2.ed.gov/rschstat/eval/tech/evidence-based-practices/finalreport.pdf.

Menager-Beeley, R. (2001, October). Student success in web-based distance learning: Measuring motivation to identify at risk students and improve retention in online classes. Paper presented at the World Conference on the WWW and Internet, Orlando, FL.

Moody, J. (2004). Distance education: Why are the attrition rates so high? *The Quarterly Review of Distance Education, 5*(3), 205–210.

Moore, K., Bartkovich, J., Fetzner, M., & Sherrill, I. (2002, June). Success in cyberspace: Retention in online courses. Paper presented at the Association for Institutional Research, Toronto, Canada.

Moore, P. B. (2001). Access and success in web courses at an urban multicultural community college: The student's perspective (Doctoral dissertation, Northern Arizona University, Flagstaff).

Morris, L. V., Finnegan, C., & Wu, S. (2005). Tracking student behavior, persistence, and achievement in online courses. *The Internet and Higher Education, 8*(3), 221–231.

Morris, L. V., Wu, S., & Finnegan, C. (2005). Predicting retention in online general education courses. *The American Journal of Distance Education*, *19*(1), 23–36.

Munro, J. (1987). The discourse of dropout in distance education: A theoretical analysis. Paper presented at the annual conference of the Canadian association for the study of adult education.

Muller, 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,* 241–261.

Nash, R. D. (2005). Course completion rates among distance learners: Identifying possible methods to improve retention. *Online Journal of Distance Learning Administration*, *8*(4).

National Center for Education Statistics, U.S. Department of Education. (2015). *College Navigator*. Retrieved from the National Center for Education Statistics website: https://nces.ed.gov/collegenavigator/?q=syracuse+university&s =all&l=93&ct=2&ic=1&id=196413#retgrad

National Center for Fair and Open Testing. (2007, August 20). *SAT I: A Faulty Instrument For Predicting College Success.* Retrieved September 10, 2015.

National Science Foundation. (2012). *Science and Engineering Indicators 2012*. Retrieved from http://www.nsf.gov/statistics/seind12/.

Ojokheta, K. O. (2010). A path-analytic study of some correlates predicting persistence and student's success in distance education in Nigeria. *Turkish Online Journal of Distance Education, 11*(1).

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

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

Parker, A. (1999). A study of variables that predict dropout from distance education. *International Journal of Educational Technology.* Retrieved from http://www.ascilite.org.au/ajet/ijet/v1n2/parker/

Parker, A. (2003). Identifying predictors of academic persistence in distance education, *USDLA Journal, 17*(1), 55–62.

Paulos, J. A. (2015, July 1). Do SAT scores really predict success? Retrieved from ABC News website: http://abcnews.go.com/Technology/WhosCounting/story?id=98373.

Public Policy Institute of California. (2014). Online courses in community colleges see major growth—but student success rates lag [Press release]. Retrieved from http://www.ppic.org/main/pressrelease.asp?i=1526.

Rovai, A. (2002). In search of higher persistence rates in distance education online programs. *The Internet and Higher Education, 6,* 1–16.

Rovai, A. (2004). A constructivist approach to online college learning. *Internet and Higher Education*, *7*, 79–93.

Shea, P., Pickett, A., & Li, C. (2005). Increasing access to Higher Education: A study of the diffusion of online teaching among 913 college faculty. *International Review of Research in Open and Distance Learning, 6*(2), 1–27.

Sheffer, S. (2014, February 18). Do ACT and SAT scores really matter? New study says they shouldn't. *PBS Newshour*. Retrieved from http://www.pbs.org/newshour/rundown/nail biting-standardized-testing-may-miss-mark-college-students/

Skorton, D., & Altschuler, G. (2012, October 29). Does Your Major Matter? Retrieved May 30, 2015, from http://www.forbes.com/sites/collegeprose/2012/10/29/does-your-major-matter/

Smith, P., & Ragan, T. (1999). *Instructional design*. New York: John Wiley & Sons.

Smith, P., & Ragan, T. (2005). *Instructional design*. New York: John Wiley & Sons.

Srinivas, K. (2012). The effect of participation in Syracuse University Project Advance and Advanced Placement on persistence and performance at a four-year private university (Doctoral dissertation, Syracuse University).

Street, H. (2010). Factors influencing a learner's decision to drop-out or persist in higher education distance learning. *Online Journal of Distance Learning Administration*, *13*(4), 1–5.

Sullivan, P. (2001). Gender differences and the online classroom: Male and female college students evaluate their experiences. *Community College Journal of Research and Practice, 25*, 805–818.

Terry, N. (2001). Assessing enrollment and attrition rates for the online MBA. *T H E Journal, 28*(7), 64–68.

Tonsing-Meyer, J. (2013). An Examination of Online Instructional Practices Based on the Learning Styles of Graduate Education Students. *Quarterly Review of Distance Education*, *14*(3), 141.

Twigg, C. A. (2009). Using asynchronous learning in redesign: Reaching and retaining the at risk student. *Journal of Asynchronous Learning Network, 8*(1), 147–155.

U.S. Department of Education, National Center for Education Statistics. (2011). *The Condition of Education 2011* (NCES 2011-033), Indicator 43.

U.S. Department of Education, Office of Planning, Evaluation and Policy Development. (2010). *Evidence-based practices in online learning: A meta-analysis and review of online learning studies.* Washington, D.C.

Valasek, T. (2001). *Student persistence in web-based courses: Identifying a profile for success.* Raritan Valley Community College, Center for the Advancement of Innovative Teaching and Learning, Branchburg, NJ.

Visser, J. A. (2000). Faculty work in developing and teaching Web-based distance courses: A case study of time and effort. The American Journal of Distance Education, 14(3), 21–32.

Wickersham, L., Espinoza, S., & Davis, J. (2007). Teaching online: Three perspectives, three approaches. *AACE Journal*, 15(2), 197–211. Chesapeake, VA: AACE.

Xenos, M. (2004). Prediction and assessment of student behavior in open and distance education in computers using Bayesian networks. *Computers & Education,* 43(4), 345–359.

Xenos, M., Pierrakeas, C., & Pintelas, P. (2002). A survey on student dropout rates and dropout causes concerning the students in the course of informatics of the Hellenic Open University. *Computers & Education*, 39(4), 361–377.

VITA

Academic Preparation

Syracuse University, Syracuse, NY (Fall 2015)
Doctorate of Philosophy, Instructional Design, Development, and Evaluation
Dissertation: *Student Characteristics That Predict Student Persistence and Performance in Online Courses and the Face-to-Face Equivalents at a Four-Year Private Northeastern University*
Chair: Tiffany A. Koszalka, PhD
Committee Members: Kalpana Srinivas, PhD, and Yildiray Yildirim, PhD

University of Maine, Orono, ME
Master of Education: Instructional Technology

Allegheny College, Meadville, PA
Bachelors of Science: Computer Science

Selected Work Experience

Syracuse University — December 2013–Present
University College
Manager of Online Programs and Services

Primary duties include: As head of online programs and services, serve as liaison between online programs and services office of University College, 10 schools and colleges across campus, the University's department of faculty development, and information technology unit. **Collaborate** with department chairs and faculty members in identifying, creating, and implementing new online courses and program opportunities. Provide **strategic leadership** in student **retention** and online education **policies,** and identify needed resources for faculty to develop and facilitate online instruction.

Accomplishments include:

- Advanced department from **infancy to three employees.**
- Implemented policies and procedures for online education across campus.
- Conceived, implemented, branded, and marketed the **inaugural meeting** of the University Partners for Online Education Strategies committed to gathering central and western New York **colleagues** of four-year private institutions to discuss common challenges, share ideas, and build a professional development network.
- **Envisioned, proposed, and constructed faculty-dedicated studio** for online course development complete with green screen, recording and editing capabilities, and Wacom tablet and screen capture technologies.
- Conceived, designed, developed, and implemented *online.syr.edu*, the **Online Programs and Services department website** providing information resources about teaching, learning, and collaboration tools available for online courses.

Onondaga Community College June 2012–December 2013
Office of Institutional Research and Planning
Director of Program Evaluation

Primary duties include: Responsible for **leadership** in designing, developing, and implementing ongoing **evaluation** of college across 45 academic departments. This included successful evaluation of the undergraduate curriculum, including context, inputs, and **process and outcomes assessment**. Completed both qualitative and quantitative data collection, analysis, interpretation, and report preparation for various stakeholders. In collaboration with faculty, administrators, staff, students, and other stakeholders, **collected and analyzed relevant data** from both internal and external resources in support of the institutional planning and decision-making process for continuous institutional improvement.

Service to the college:

- Appointed as a team **coleader** for the Career Pathways initiative, which is identified as a key goal in the 2011–2016 strategic plan.
- Served as **provost's designee** on the **Learning Outcomes and Assessment Committee** (LOAC).
- **Selected by peers** to serve as a two-year (2011–2013) representative and **cochair** for the Onondaga Community College Administrators Council (OCCAC).
- Selected as a 2011 **Assessment Fellow** to coordinate survey efforts; systematically gather, analyze and interpret data; and use results of assessments to enhance student learning.
- **Selected by peers** to serve a three-year term (2010-2014) on the Chancellor's Award Committee.
- Served as distance learning **liaison** on the Academic Technology Coordinating Committee (ATCC).
- Served on the PowerStart committee, which is committed to first-year **student success**.

Accomplishments include:

- Formally trained in advanced project management techniques.
- Worked with 175 faculty and 50 department chairs and discipline coordinators to **refine course and program level educational objective statements and learning outcomes**.
- **Assisted** 175 faculty and 20 academic leaders in their review, **interpretation,** and use of **assessment findings**.
- Generated monthly and specialized reports, surveys, forecasts, and trend analyses on the **effectiveness** and **improvement** of **educational programs** and **administrative/support services**.
- Coordinated the design, validation, implementation, analysis, interpretation, and reporting of activities that focus on **outcomes assessment**, **curriculum,** and **program review** for 45 academic programs.
- Developed analytical reports to support **accreditation** activities, specifically institutional effectiveness and the **assessment of student learning**.
- Developed and provided training and consulting for faculty and administrators in the **areas of assessment**, **program review**, use of web-based reporting tools and department-level planning.

Onondaga Community College April 2010–June 2012
Office of Distance Learning
Assistant Director of Distance Learning

- Developed and **fostered yearlong relationships** with 100 faculty developing online courses and guided them through conception, design, development, implementation, and evaluation.
- Designed, developed, and implemented faculty **professional development** workshops on instructional design and theory topics as well as trends in distance education.
- Provided three separate detailed course reviews throughout the design and development process for each faculty partner.
- Ran, monitored, and compiled online persistence and enrollment **data for analysis**.
- Developed and maintained budget, including faculty payment.

CDMiConnect, LLC March 2010–April 2010
Consultant: Instructional Designer

- Served as sole instructional design expert and drafted instructional design components based on a **document analysis** for a project bid with Pfizer.
- Designed a comprehensive **educational program** for rheumatoid arthritis patients.
- CDMiConnect, LLC, was awarded the project on April 19, 2010.

Syracuse University October 2008–February 2009
Office of Professional Research and Development
Consultant: Instructional Designer

- Researched, developed, and assessed a **training program** for teacher-mentors using PBS Teacher Line: Peer Connection.
- Conducted a pilot test, administered and **developed survey**.
- **Collected and analyzed data** to make revisions to the training program in order to meet program's goals.

ProLiteracy Worldwide January 2007–April 2007
Consultant: Program Designer

- Served as **lead** instructional designer among a team of subject matter experts.
- Selected appropriate activities and instructional strategies aligned with **course objectives** to develop online courses for literacy instructors.

Selected Teaching Experience

New York Chiropractic College Fall Semester 2010–Present
Master of Science in Human Anatomy and Physiology Instruction
Adjunct Assistant Professor

- Worked in **collaboration** with colleague to **design and develop** four course **curriculum** series for the Masters of Science in Human Anatomy and Physiology Instruction program to be **taught fully online;** it launched in fall 2010.
- Delivered course content each trimester **fully online** to transform the student into a highly effective instructional specialists for the undergraduate lecture hall and laboratory.
- Designed and developed **three, 15-week courses** titled, Instructional Theory and Practices: Foundations of the Classroom; Instructional Theory and Practice: Elements of Course Development; and Instructional Theory and Practice: Designing and Developing for Lab and Online Learning Environments.

Selected Academic Publications and Presentations

Bull, K. Z. (July 2015). Distance Education State Authorization. Presented at the Administrative Mangers Institute of Cornell University, Ithaca, NY.

Bull, K. Z., Frasciello, M. J., & Williams, V. (March 2015). Hybrid Strategies for Centralized/Decentralized Online Program Support and Services. Presented at the 100th Annual Conference of the University Professional and Continuing Education Association, Washington, DC.

Bull, K. Z. (September 2011). Infuse Learner-Centered Teaching into the Online Environment. Presented at the State University of New York Center for Professional Development, Albany, NY.

Bull, K. Z. (May 2011). Rubrics: An Overview and the Details. Presented at the Conference on Instruction and Technology, Oneonta, NY.

Bull, K. Z. (January). Are you trendy? Rubrics are "in" this year. Onondaga Community College Teaching Center Newsletter, 2011(1), 1–4.

Bull, K. Z. (2010, September 10). Poster week: Karen Zannini Bull on making good evaluation decisions (Web log message). Retrieved from http://aea365.org/blog/?p=1595

Bull, K. Z. (November 2010). Iterative Reasoning: The Art of Determining Good Enough: Instructional Design and Evaluation Meet. Presented at the 24th Annual Conference of the American Evaluation Association, San Antonio, TX.

Bull, K. Z. (November 2009). Are There Important Differences Between Curriculum Evaluation and Program Evaluation? Presented at the 23rd Annual Conference of the American Evaluation Association, Orlando, FL.

Bull, K. Z., & Smith, N. L. (November 2008). Conceptual and Empirical Problems in Evaluating Evaluation Theory. Presented at the 22nd Annual Conference of the American Evaluation Association, Denver, CO.

Zannini, K. (April 2008). Issues in the Conceptual Study of Evaluation. 2008 Annual Proceedings. Presented at the 22nd Annual Edward F. Kelly Evaluation Conference. Ontario, Canada

Zannini, K. (April 2007). Does Accreditation Lead to Long-Term Institutional Change? 2007 Annual Proceedings. Presented at the 21st Annual Edward F. Kelly Evaluation Conference. Ottawa, Canada

Fried, A., Lee, Y., Zannini, K., & Koszalka, T. A. (October 2006). From Design Theory to Development Practice: Developing a Stronger Understanding of Our Field. 2006 Annual proceedings (Vol. 2). Presented at the 29th Annual Convention of the Association for Educational Technology and Communication, Dallas, TX.

Selected Professional and Community Activities

Women's Fund	January 2014–Present
▪ Board of Directors	
University Professional and Continuing Education Association	December 2013–Present
▪ Secretary, New England Region	March 2015–March 2017
▪ Awards Committee	January 2013–Present
Rosamond Gifford Zoo	January 2012–Present
▪ Education Committee Member	
American Evaluation Association	January 2007–Present
▪ Theories of Evaluation Topical Interest Group Co-Chair	August 2010–December 2013
▪ Graduate Student Representative for Membership Committee	November 2008–November 2010
▪ Graduate Student TIG Board Member	November 2008–November 2010
American Education Research Association	January 2007–Present
Association for Educational Communications and Technology	August 2005–Present