Student Outcomes in Online and Face-to-Face Classes at a Hispanic-Serving Institution (HSI)

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Student Outcomes in Online and Face-to-Face Classes at a
Hispanic-Serving Institution (HSI)

A Dissertation
Presented to
the Faculty of the Morgridge College of Education
University of Denver

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

by
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Advisor: Maria Salazar
Abstract

As online course enrollments are increasing in higher education in the United States, it is increasingly important to understand student course outcomes in these classes, particularly at Hispanic-Serving Institutions (HSI), where there has been limited previous research. This current study examines online course outcomes in the form of student course grades and student withdrawal rates as compared to outcomes in face-to-face courses. The setting for the study is Russell University, a public university in the Rocky Mountain west, and an HSI. Data used in this study came from a large, deidentified data set of all enrollments in any course offered in both online and face-to-face formats during the 2017-2018 and 2019-2019 academic years.

Baseline results of this study indicate that students in online classes have significantly higher course grades, and non-significantly different withdrawal rates than do students in face-to-face classes. The study tests three different propensity score methods for validity and sensitivity to select a statistical method that is the best match for the data in controlling for 15 student covariates. The final statistical method chosen is a near-neighbor 1:2 propensity score analysis to control for these confounding covariates in order to balance the online and face-to-face enrollment groups. After balancing the groups using the near-neighbor 1:2 propensity score method, results indicate that there is
a non-significant difference between online and face-to-face course enrollments in terms of student grades. However, after balancing, there is a significantly higher withdrawal rate among online students than face-to-face students. While promising, these results need additional confirmation from future research, as they remain highly sensitive to hidden bias from missing variables.

These results have important implications for students, faculty and administrators at an HSI to ensure equitable access to education in all course modalities. Online faculty should ensure that they intentionally build community in online classes and invite students to participate in high-impact practices such as research with their instructors. Administration should continue to provide faculty with collaborative instructional design support as they create effective online learning spaces. Finally, administration should provide access to personalized online student services such as advising and mental health resources to help students feel connected to the campus community.
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Chapter 1 – Introduction

Research Problem and Significance

Online course enrollment has been increasing at United States institutions of higher education in the last decades, with 11 percent of students enrolled at public institutions attending exclusively distance education courses as of fall semester 2017 (National Center for Education Statistics (NCES), 2018). Additionally, among undergraduate students at four-year, public institutions, 31.7% of students enrolled in at least one distance education course in fall 2017 (NCES, 2018). Nation-wide online course enrollment has increased steadily from 9.6% of in 2002 to 31.6% in 2016 (Allen & Seaman, 2014; Seaman, Allen & Seaman, 2018). This increase in online course enrollment has happened in spite of the trend of enrollment decline in the United States since 2012 (Seaman, Allen & Seaman, 2018).

After seeing many years of increasing online enrollments, institutions of higher education around the United States were suddenly forced entirely online in March 2020 in the wake of the COVID-19 pandemic, providing all students and faculty with an unexpected e-learning environment and decreased governmental restrictions on distance learning (Green, 2020). Preliminary opinion pieces suggest that this shift to online education for all colleges in the US will increase funding and attention for educational technology, and will drive institutional priorities to develop and increase their online and
blended course offerings in the future (Kim, 2020; McCauley, 2020). Given both these long-term and emergent trends, students, faculty members, and university administrators can all benefit from understanding the student outcomes in online classes. This understanding is particularly important at Hispanic-serving institutions, where there has been limited research on the implications of online learning and the impact on student course outcomes. This trend of increased online course enrollments makes it important to understand student course outcomes in online classes and how they compare to outcomes in face-to-face classes.

The Online Learning Consortium (OLC) provides definitions for online, hybrid and face-to-face classes. According to this group, in an online class students complete all work online, with no required in-person meetings on campus. A blended or hybrid class mixes in-person class sessions with online activity, replacing face-to-face meetings with online materials or activities. Finally, a face-to-face course is one where the course meets regularly on campus in scheduled class sessions (Sener, 2015).

There is a wide variety of research findings related to the effect of online course enrollment on student outcomes. One particularly relevant voice in the field of online learning and outcomes is Russell (1999) who defined the “no significant difference phenomenon” indicating no difference among course outcomes across course modalities. Russell asserts that hundreds of examples of research studies document statistically similar outcomes in online and face-to-face classes. As an example, Hurlbut (2018) and Tseng and Walsh (2016) both found no significant difference in course grades based on
class modality (online, hybrid, or face-to-face format) at two different universities in the United States. While these studies provide strong evidence that in some cases there is no statistical difference in course outcomes, there are also contrasting publications that indicate a significant effect of online course enrollment on student course outcomes such as grades, exam scores, or course GPA. In contrasting studies, researchers found data that suggest a positive effect of student enrollment in face-to-face classes (Gregory, 2016; Johnson & Palmer, 2015). Moreover, other research has suggested the opposite - that there is a positive effect of student enrollment in online classes on student course outcomes (Bunn, Fischer & Treba, 2014; Kaupp, 2012; Verhoeven & Wakeling, 2011).

Research in this field shows a variety of results on student course outcomes, including: (a) no significant difference between online and face-to-face classes, (b) positive affect of online course enrollment, and (c) negative impact of course enrollment.

These inconclusive results are particularly important in light of their observational research design, and their inability to control for selection bias. Research that does not involve randomized control trials cannot effectively control for selection bias, particularly in a case where students are self-selecting into different course types (Coates & Humphreys, 2004; Koch, 2005).

In order to understand student outcomes, it is important to control for selection bias in conducting rigorous research. Randomized control trials are often impractical in an educational setting, where students in higher education choose to enroll in the course modality that they prefer. While there has been research on undergraduate student
outcomes in online and face-to-face classes at public four-year institutions, very little of it attempts to control for selection bias, that is: students self-select into online or face-to-face sections of a class. When students self-select into class sections of different modalities, this can introduce selection bias. Self-selection does not allow the researcher to control for personal student characteristics in each course modality without a randomized control trial. Selection bias is important because studies that focus only on course outcomes but not accompanying student characteristics “do not tell us why some students achieve better grades than others when they utilize distance learning” (Koch, 2005, p. 2). These studies do not indicate if student characteristics have an impact on course outcomes. Others also recognize the problem that “self-selection into online classes is an important issue in the assessment of the effectiveness of online education. Failure to account for the effects of selection leads to biased and inconsistent coefficient estimates.” (Coates & Humphreys, 2004, p. 545). Conclusive research that uses statistical analysis to control for covariates such as race, gender, and other demographic, personal, and academic factors is limited. Smith (2017) found five studies that used rigorous methods to control for selection bias in postsecondary online course outcomes.

Results of studies that control for race also show different results. Some studies suggest that race is a significant factor in online course outcomes, with lower outcomes for non-white students (Kaupp, 2012; Koch, 2005). Other studies indicate that race is not a significant contributor to course outcomes (Waschull, 2001). This distinction is particularly important at institutions that serve high numbers of Students of Color, such
as Hispanic students. There is a paucity of research related to online course outcomes at Hispanic-Serving Institutions (HSI), where it is important to understand the educational outcomes of these students. Literature related to student outcomes in online classes at HSIs is limited, and includes research that is more related to student perceptions of online classes than course outcomes such as grades or assessment scores (Lu & Cavazos Vela, 2015). Only two studies have specifically addressed student course outcomes in online classes at HSIs (Camara, 2016; Wladis, Conway, & Hachey, 2015), indicating a need for additional research in this area. The researcher will discuss these findings further in the literature review for this study.

Online course enrollments have been increasing in the United States, while face-to-face enrollments have been decreasing (Seaman, Allen & Seaman, 2018). In order to understand the effects of this enrollment change research that rigorously controls for student demographic, academic, and personal characteristics in a quasi-experimental design is necessary. The current study will attempt to examine effect of enrollment in different course modalities through a rigorous study of student course outcomes in online and face-to-face courses at a four-year, public, HSI.

**Study Purpose**

The purpose of this study is to explore online course outcomes, specifically average course grades and course withdrawal rates, at a four-year, public Hispanic-Serving Institution. The current study will examine course outcomes in online and face-to-face classes. The researcher will control for student demographics, academic
performance, and external factors such as marital status to overcome selection bias created by students self-enrolling in different course modalities.

The research for this study will take place at Russell University (pseudonym), a public, four-year undergraduate institution in the mountain west area. Russell was founded in 1965 to serve an urban population, with steady growth of student numbers during that time. By 2020, Russell had nearly 20,000 students enrolled in more than 100 majors, eight graduate programs, and 34 certificate programs. Russell offers face-to-face and online courses in a wide number of topics, including letters, arts, sciences, professional studies, business, education, and hospitality. Student grades are typically assigned as a course letter grade, using a plus or minus system (A, A-, B+, etc.). Some limited exceptions allow a pass/fail grading option for certain courses and count only for elective credit. Russell’s website states that “Major, minor, general studies and other class required for a degree or for teacher licensure may not be taken on a pass/fail basis.”

The student population at Russell University is diverse, and non-traditional. According to the Russell website, “more than 95% of our students are from [our state]; 46% of undergraduates are students of color; 56% of [Russell University] undergraduates are the first in their family to go to college; the average undergrad is 25 years old.” Additionally, nearly 80% students at Russell work full or part time. Due to this diverse student population, this institution became a Hispanic-Serving Institution (HSI) in the spring of 2019. The United States Department of Education defines HSI’s as institutions that enroll at least 25% Hispanic students (Hispanic-Serving Institutions, n.d.), and
according to their institutional website, Russell University met that requirement in 2019. Additionally, 44.7% of the undergraduate population at Russell University were Students of Color at that time. In addition to serving Students of Color, this institution enrolls a unique student body in other ways. According to the Russell University information page on their institutional website, as of fall semester 2018, 49.1% of students were first-generation college students, and 31.5% were Pell grant eligible. The average age of students at this university was 25 during the fall of 2018.

In part because of the demographics of the institution, online learning is a priority for the university. For example, according to the Associate Vice President of Online learning at Russell, during the 2018-19 school year, 24% of all course enrollments were in online classes, showing a continued trend of increased course enrollment since online classes were first offered at the institution. As of fall 2018, 38.9% of students were enrolled in one or more online classes (AVP, personal communication, July 18, 2019). These online enrollment trends echo national online course enrollment at a public institution with a non-traditional student population.

**Research Questions**

This study will examine the effect of enrollment in online classes as compared to face-to-face classes on student outcomes after controlling for student demographics, academic markers before entering college, academic performance in college, and other external factors. It will specifically examine the extent to which online courses affect the
academic achievement of students in an HSI. All classes offered at Russell University in both a face-to-face and online format will be included in this study.

R1: To what extent does enrollment in a fully online class as compared to face-to-face classes affect course grades for undergraduate students who complete the course?

R2: To what extent does enrollment in a fully online course as compared to face-to-face classes affect course withdrawal rates for undergraduate students?

**Research Design and Methodology Overview**

Data for this research study came from a dataset at Russell University that included undergraduate students enrolled in courses offered in both online and face-to-face modalities over a two-year period starting in fall 2017 to spring 2019. Any undergraduate course offering available in both online and face-to-face modalities during this period was included in the study. The business intelligence office at Russell University provided this data set to the researcher.

To answer the research questions, the researcher performed propensity score analysis using the following steps: (a) estimate propensity scores using near-neighbor matching, a Mahalanobis distance metric, and an optimal matching technique; (b) perform Rosenbaum’s (2002) sensitivity analysis to determine the robustness of each of the estimating models; (c) select the most appropriate and robust model for the data; (d) assess the effect of online course enrollment on course grades (R1) and course withdrawal rates (R2) by using a two-sample $t$-test to determine the effect of course enrollment.
**Strengths and Limitations of the Proposed Study**

This study expands on the current research in the field by examining online course outcomes as compared to outcomes in face-to-face classes at an HSI, which has not been the focus of previous research. Additionally, this observational study used a propensity score statistical method to control for student characteristics as covariates as a control for selection bias. Only one previous study (Smith, 2017) has used a similar methodology on a large scale to determine relative student outcomes in online courses. Smith focuses on the overall population at the University of North Carolina College system, and does not reference a Hispanic-serving Institution. This current research will help to fill in a gap in the literature.

The weaknesses of this study include a limited scope, as it only examines data from one HSI. Additionally, data were taken from a university data set rather than a survey designed by the researcher. While this allows for a much larger number of data points, it also limits the information available to institutionally collected data. This means that when aligning the statistical analysis with the Tinto (1973, 1995) and Rovai (2003) models of student integration, there was not an exact match between the theoretical model and available data. Additionally, while course grades and withdrawal rates are readily available in an institutional data set, other measures of student learning such as exams, projects, and personal reflections were excluded from the study.

Research that includes small sample sizes in a specific course or subject allows for details about class type, instructional method, and other specifics about online
learning in that specific class or subject (Bunn, Fischer & Treba, 2014; Johnson & Palmer, 2015; Verhoeven & Wakeling, 2011). Research with large sample sizes does not have the same ability to describe the individual course and setting (Amro, Mundy & Kupczynski, 2015; Atchley, Wingenback, & Akers 2013; Cavanaugh & Jacquemin 2015). The current research study is strong in including a large sample size, but because classes in more than 150 subject headings are included in this research at Russell University, it is impossible to include more detail about individual courses and characteristics about the learning environment that may have a significant impact on student course outcomes. The lack of specific details about individual course design is a limitation of using a large secondary data set rather than a smaller, primary data set or survey.

Summary

While online course enrollment has been increasing across the United States, research on the topic of student outcomes has been inconclusive. There has been very limited research that controls for student characteristics to account for selection bias, which is important as students self-enroll in different class modalities rather than being randomly assigned to a class. Additionally, there has been limited research related to online course outcomes at Hispanic-Serving Institutions.

The current study attempts to fill in a gap in the literature by exploring online course outcomes at a public, four-year HSI. Russell University provided institutional data related to student characteristics and course outcomes. The researcher analyzed the data
by using a propensity score analysis and sensitivity test to examine student outcomes related to course grades and withdrawal rates.

**Definition of Terms**

*Course Modality or Delivery Modality*

In the context of this paper, course or delivery modality will refer to the format in which a course is taught. Typically, this refers to online, face-to-face, or blended formats.

*Blended or Hybrid Course*

“Online activity is mixed with classroom meetings, replacing a significant percentage of, but not all required face-to-face instructional activities” (Sener, 2015).

Specifically at Russell University, hybrid courses are defined as a course that “A Hybrid class provides some instruction on . . . campus or another location at scheduled meetings times in a designated location. The rest of the instruction is online” (Russell website).

*Face-to-face or Classroom Course*

“Course activity is organized around scheduled class meetings” (Sener, 2015).

*Online Course*

“All course activity is done online; there are no required face-to-face sessions within the course and no requirements for on-campus activity” (Sener, 2015).

Specifically at Russell University, online classes are defined as “An Online class does not require students to come to . . . campus for any purpose, nor does it require them to go to a site where exams or other activities will be proctored” (Russell website).
**Propensity Scores**

“The propensity score is defined as the probability that an individual in the combined sample of treated and untreated units receives the treatment, given a set of observed characteristics.” (Ryan, Kaufman, Greenhouse, She, & Shi, 2015, p. 291)

**Hispanic-Serving Institution (HSI)**

The US Department of Education defines an HSI as “an eligible institution; and has an enrollment of undergraduate full-time equivalent students that is at least 25 percent Hispanic students.” (Hispanic-Serving Institutions, n.d.).
Chapter 2-Review of Literature

Introduction

Student integration theory indicates that student demographic, academic, and institutional factors all contribute to course outcomes such as grades and student retention (Tinto, 1975, 1993). There is a large body of literature related to outcomes in online and face-to-face classes, with mixed results of the impact of online classes on student course grades (Bunn, Fischer & Treba, 2014; Gregory, 2016; Johnson & Palmer, 2015; Kaupp, 2012; Verhoeven & Wakeling, 2011). These studies largely do not control for the selection bias inherent in student enrollment in different course modalities. A few studies have attempted to control for this selection bias on an institutional scale, but none have been completed at a four-year Hispanic serving undergraduate university (Smith, 2017; Xu and Jaggars, 2011a, 2011b, 2013).

First, this chapter will begin by exploring the conceptual framework of person-environment interaction theory and student integration theory and how they apply in an online environment. Second, the focus will move to current research on online course outcomes through a systematic review of the literature, and how it relates to student outcomes. Third, this chapter will also examine the state of current literature concerning Tinto (1993) and Rovai’s (2003) complex model of the interaction of student characteristics and course outcomes, and research that explores a wide range of
demographic and academic factors to control for selection bias. Fourth, the chapter summarizes the value of propensity score statistical models in analyzing data. Fifth, this chapter covers the current literature related to online course outcomes at Hispanic-Serving institutions. Last, this chapter offers suggestions for future research.

**Conceptual Framework**

**Person-Environment Interaction Theory**

Lewin (1936) developed the person-environment interaction theory (PEI theory) which posits that behavior is a result of the interaction between personal characteristics and the specific environment of study. Hunt (1979) goes on to suggest that in education “it is less important that we know all the parts, than that we acknowledge that several parts must be considered and that the relationship between the parts is critical to understanding a person” (p. 1.16). The relationship between personal student characteristics and their environment is a contributing factor to understanding success rates in higher education. Many factors are important to understanding the college environment and its relationship to personal student characteristics.

**Developmental Ecology**

One branch of PEI theory that focuses on the many factors exerting an influence on college students is developmental ecology theory, first developed by Urie Bronfenbrenner (1979). This theory focuses on individual students and their characteristics rather than the culture influencing them. Bronfenbrenner (1996) argues that human development is based on a complex system of interaction, which examines an
individual’s relationship with many facets of their environment, and the impact of those facets on personal development. Developmental ecology is a broad theory of human development, although it does have implications in an educational environment, as student relationships in and out of the university setting have an impact on academic performance.

**Student Integration Theory**

Tinto’s student integration model (SIM) is one theoretical model that emerges from developmental ecology with a specific focus on higher education. It reveals the combination of environmental and personal factors that affect student persistence decisions (Evans et al., 2010). This model examines the reasons why students decide to persist in or drop out from higher education. Tinto’s model explores personal

![Figure 1](image-url)  
*Figure 1. Tinto’s (1993) student integration model. This figure represents the relationship between student characteristics and academic persistence.*
characteristics such as family background and personal attributes, together with academic performance at the university and involvement in the university community (Tinto, 1975, 1993).

The SIM looks specifically at four categories, seen in figure 1, that contribute to a student’s educational outcome, defined by Tinto as their decision to persist in or to depart from higher education. The first category is pre-entry attributes, which consist of family background, skills and abilities, and prior education. The next category relates to goals and commitments, specifically academic intentions, institutional commitments, and external commitments. The third group of Tinto’s model that influences educational outcome is institutional experiences, including both formal and informal experiences at the university. Formal experiences consist of academic performance and faculty interactions. Informal experiences are extracurricular activities and peer group interactions. The fourth category is integration, which explores student academic integration and social integration with peers. Tinto argues that student outcomes are a result of a complex combination of their personal characteristics, goals and commitments in and out of the university, their experiences while at the university, and how well they integrate socially and academically in college. Tinto developed this model prior to the onset of online classes but does form the foundation of other theoretical work with online and distance education.
**Critiques of Student Integration Theory**

While Tinto provides foundational work for understanding student persistence, other theorists have criticized the SIM as culturally limiting. One example is Tierney (1993) who argues that the SIM is most relevant for students who are part of the dominant culture, and that the model does not extend to minoritized students. Tierney also criticizes the individualistic aspects of the SIM that posit that a student by themselves is responsible for their persistence at college, rather than recognizing the collectivist role that a group culture plays in that decision, which is particularly relevant for non-dominant cultures.

Another shortcoming of the SIM is that it fails to account for the role students might play in their own academic and social integration (Maldonado, Rhoads, and Buenavista, 2005). These authors proposed a new framework that accounted for available cultural and social capital while focusing on collectivism. Through these individual and group resources, students can be agents of institutional change as they influence other students and their collective academic environment, even as the environment has an impact on them.

Although the support of students themselves on their peers’ outcomes is important, another critique of the SIM is the failure to account for the importance of support and encouragement from many significant others (Nora, 2001). Nora specifically describes the influence of significant others during high school to help students make the transition to college, as well as the influence of academic and family members who
provide student support after starting in college. While students’ decisions to graduate from college are related to academic and institutional factors, the degree of influence from significant others also has a direct impact on student success and persistence in college.

Many other theorists have specifically examined persistence models for Hispanic students (Rendón, 1981, 1995), for diverse ethnic and gender groups (Nora & Cabrera, 1996), for low-income and diverse cultural groups (Bensimon, 2007), and ethnic minority student success (Museus, 2011; Museus & Ravello, 2010). These theories are more specific to their particular academic and cultural contexts, and branch out from the foundation of the SIM model in anticipating student success and persistence in higher education.

**Student Integration in Distance Learning**

Despite the critiques of Tinto’s model and more recent literature that explores specific contexts for retention, the SIM is considered a seminal work in the field of college student retention. The idea that many factors contribute to the whole picture of student success is important in higher education. Additionally, there is no specific theoretical model for student grades and retention in online classes. Only one researcher has synthesized Tinto’s model and other literature related to online and distance education student outcomes, providing a functional framework for understanding persistence in the context of this work (Rovai, 2003). Because of the seminal nature of Tinto’s work, and the fact that it forms the foundation of theory used to assess student
persistence in online and distance learning, the current research uses the Tinto’s SIM as the conceptual framework for the study, despite the critiques that surround Tinto’s model.

In a distance learning format, Rovai (2003) suggests that with the increase in non-traditional students enrolling in higher education, and their likelihood of enrolling in distance education, it is important to understand these students’ persistence decisions. With this goal in mind, he created a composite model based partly on Tinto’s SIM theory to suggest an understanding of persistence decisions for distance or online students.
Rovai’s (2003) model presents four categories of relevant student characteristics, seen in figure 2, which should be considered when researching student persistence in online classes. These categories include student characteristics prior to admission, student skills prior to admission, external factors after admission, and internal factors after admission. Student characteristics prior to admission include, but are not limited to: age,
ethnicity, gender, and academic performance prior to college. Student skills that influence a decision to persist include computer literacy, information literacy, time management, reading and writing skills, and computer-based interaction. External factors in Rovai’s model include student financial status, employment, family obligations, outside encouragement, and life crises. The final category of internal factors includes academic performance, social integration, and goal commitment.

In both Tinto (1993) and Rovai’s (2003) models, it is important to note that student outcomes in higher education are related to many personal and academic factors that contribute to a complex system of interactions that all influence a student’s success in online or distance classes. Because SIM theory states student characteristics have an impact on student outcomes in higher education, it is important to explore what other research has found about the relationship between these characteristics, and student outcomes in online courses. The next section of this chapter will specifically address Hispanic student success in higher education, and success at Hispanic-serving institutions before moving toward a systematic review of the literature related to online student outcomes.

**Hispanic Student Outcomes in Higher Education**

The National Center for Education Statistics (2012) published a concerning report about student persistence indicating that of Hispanic students who enrolled in a four-year college program, only 52% earned some type of postsecondary degree such as bachelor’s degree, certification, or associate’s degree during a five year period. This rate was 21%
less than the completion rate for White students during the same timeframe. This lower persistence rate is concerning because of long term implications for employment, salary, and social equity in Hispanic communities. The NCES research suggests that Hispanic students who started at public, four-year institutions as full time students were more likely to achieve their academic goals than those at private institutions, community colleges or as part-time students.

Some factors that have an influence on Hispanic student persistence rates at community colleges include parental education as a form of social capital, delaying enrollment after graduating from college, and ability to enroll full-time (Crisp & Nora, 2010). Hispanic students’ persistence suffers when they lack social capital to help them succeed as a first-generation college student, and when they need to delay enrollment in college or enroll part-time, usually because of financial concerns that requires them to work before entering college, or during their academic experience. Crisp and Nora (2010) also indicate that attending an HSI has a positive impact on student retention for Hispanic students, possibly because campus climate is more conducive to a positive cultural and educational experience (Hurtado & Ponjuan, 2005). Attention to Hispanic-serving institutions and their impact on student success rates has been increasing over the last 10 years.

Excelencia in Education (2019) reports that from 2007 to 2017, there has been a 98% increase in the number of HSIs in the United States, with a total of 523 in 2017. The HSI designation allows institutions to request grant funding to support students, and
many have requested funds to aid students in transferring from a two-year to a four-year institution, or to outreach to K-12 schools to encourage Hispanic students to prepare for college. Despite the goal of HSIs to better serve a Hispanic population as they attend college, evidence suggests that enrollment at an HSI may not have a positive effect on student graduation or persistence rates. Kelly, Schneider, and Carey (2010) found that at HSIs, it appears that the gap between Hispanic and White student performance is decreasing. However, this closing gap is more related to the lower rate of White student graduation at HSIs than an increased graduation rate for Hispanic students. Other research suggests that after controlling for covariates such as income, there is no significant impact of enrollment at an HSI on Hispanic student performance (Flores & Park, 2015).

Given the lower success and persistence rates for Hispanic students, our institutions of higher education need to do better at providing an equitable educational experience that supports students as they move towards graduation, particularly at an HSI. As online course enrollments continue to increase in the United States, these distance learning classes need to provide equitably for all students, and ensure that Hispanic students can move towards graduation effectively in both online and face-to-face formats.

The purpose of this literature review is to examine current research on online student outcomes to determine if research on student success rates in online classes accounts for the influence the factors provided by Tinto and Rovai. In the sections that
follow, the researcher will address a systematic review of research in the online learning field and how it relates to Tinto (1993) and Rovai (2003) and their belief that student characteristics relate to course outcomes. Following the review of literature related to the SIM, the researcher will examine research that examines student outcomes in online classes at Hispanic-serving institutions.

**Literature Review**

*Methods for Searching*

This section will address the methods for conducting a systematic review of the literature related to online learning outcomes in higher education. First, it will address the search terms and parameters for inclusion in the literature review before discussing how articles were reviewed for inclusion. It will then detail some of the major themes extracted from the articles included in this research, and will provide analysis of the outcomes listed in the articles.

For this literature review, the researcher investigated previous research on student outcomes in online classes by searching the ERIC database using search terms related to three categories: (a) success rates, grades (scholastic), and educational indicators; (b) online education, or distance education; (c) higher education, or postsecondary education. This search identified 1587 results, which were reduced using the following inclusion criteria:
• Published between 1994 and 2018. The start date of 1994 was the year that CALCampus was created, and is believed by some to be the beginning of online education (Tom, 2017).

• Related to undergraduate students in higher education. Higher education was defined as two-year or four-year institutions, including community colleges, public or private institutions of higher education (IHEs), including both non-profit and for-profit institutions. Alternatives such as concurrent enrollment options at a high school were not included in this literature review.

• Related specifically to quantitative measures of success rates in online courses. Qualitative measure alone were eliminated from the study, as was research that focused on only hybrid or blended course outcomes, with no data from online classes.

• Course outcomes were related to student characteristics and not pedagogical innovations in class delivery.

• Research was conducted in the United States.

An initial title review of the 1,587 results using these selection criteria reduced the number of articles to 132. A further screening by reading the abstracts for these articles reduced the total to 41. This second screening mainly eliminated articles related to graduate online classes or courses taught outside of the United States, according to established selection criteria.
While reading and reviewing the studies, the researcher extracted data related to student demographic information, the type of educational institution, the number of participants in the study, the student characteristics or other internal or external factors related to Rovai (2003) and Tinto’s (1993) integration models, and the success rate of students.

Overall, these research studies had small sample sizes that examined multiple sections of a particular class subject. Only eight of 41 studies had an $n$ of more than 1,000, with the largest sample size of 4.5 million (Kaupp, 2012). Some measure of course grade was the primary measurement of course outcome, and these studies included course letter grade, course percentage grade, course success rate of A, B, or C grades in the class, and course GPA. Other measures of course outcomes included course exams, scores on national tests, and project or assessment grades. In this sample of 41 research studies selected for inclusion, results varied widely, and are discussed in the sections that follow.

**Results of Literature Review**

Significance of course outcomes in online versus face-to-face classes. Of the 41 articles, 35 clearly noted a statistical result for course outcomes by comparing variables between online and face-to-face classes. The remaining six articles did not focus on overall course outcomes between online and face-to-face classes, but had a different independent variable. Five of these six articles focused on course outcome for different groups of students by race, gender, and other characteristics (Dotterweich & Rochelle
2012; Gregory, 2016; Koch, 2005a, 2005b; Kupczynski, Brown, Holland & Uriegas, 2014). One article indicated a mixed result, with six of ten measures showing higher scores in the online class, and the remaining four showing better results for face-to-face classes (Thrasher, Coleman, & Atkinson, 2012).

Of the remaining 35 articles that specifically examined the differences between student outcomes in online versus face-to-face classes, results were mixed, with 21 studies showing no significant difference among class modalities, eight showing significantly higher results in online sections, and six showing significantly higher results in face-to-face classes. Studies that show no significant difference among course outcomes are consistent with the no significant difference phenomenon (Figueira, 2010) that indicates no difference among course outcomes across course modalities. That phenomenon is also visible in the current literature review, with over half of the articles included demonstrating no significant difference between online and face-to-face course outcomes. These results are summarized in Table 1.

**No Significant Difference.** Each of the studies that demonstrates no significant difference comes from a study with a relatively small sample focused on a specific subject ranging from accounting and management (Dellana, Collins & West, 2000; Gutierrez & Russo, 2005; Rivera & Rice 2002) to nursing (Leasure, Davis, & Theivon, 2000), psychology (McDonnough, Roberts & Hummel, 2014; Waschull, 2001) and science and math courses (Reuter, 2009; Summers, Waigandt & Whittaker, 2005; Werhner, 2010). The number of data points in these studies range from 26 (Tseng &
Walsh, 2016) to 1907 (Euzent, Martin, Moskal & Moskal 2011). Although there are many studies in this literature review that suggest no statistical difference among class modalities, there were 14 studies that indicated a significant difference between groups.

**Higher Face-to-face Outcomes.** Of the 14 studies that noted a significant difference, eight found that online students performed better on measures of course outcome, and six found that face-to-face students performed better on course outcomes than their online counterparts. Among those studies that found that face-to-face outcomes were higher, most were small studies with fewer than 350 participants, however, one study examined course outcomes at California community colleges, with 4.5 million data points (Kaupp, 2012). This study found significantly higher course letter grades for students in face-to-face classes than for online students. The gap in performance was particularly notable for Latinx students, who did worse in online classes than did their White peers. The results of this study were echoed in five other studies that found similar performance results.

The other five studies that showed better performance in face-to-face classes indicated similar results, but did not test for the impact of race, and had much smaller sample sizes than the Kaupp (2012) study. These studies had different ways of measuring student performance across class modalities. Three used some form of course grade, including overall success rate as measured by a grade of A, B, or C in the class (Verhoeven & Wakeling, 2011), a combination of course grade and overall GPA (Bunn, Fischer & Treba, 2014), and a combination of final course grade percentage and grades
on midterm and final exams (Johnson & Palmer, 2015). The remaining two studies used course or national exam scores for their research, but still showed the same trend of lower outcomes in online classes. One group of researchers used a combination of exam grades and pretest scores to look at student improvement during the course, with higher final exam scores in face-to-face classes (Arias, Swinton & Anderson, 2018). A different study required students to take a national economics exam as a way of normalizing outcome measurement across three institutions teaching similar classes (Coates & Humphreys, 2004). In this case, national exam scores were significantly lower in the online classes. Results from the studies mentioned in this section indicate that face-to-face students have significantly higher course grades and exam scores than do online students.

**Higher Online Outcomes.** In contrast, this review found eight research articles that suggested higher success rates in online classes, with poorer results for face-to-face students. Overall, the studies themselves looked similar to those with opposite results. Five of the eight studies had smaller sample sizes, with three studies with 5,000 or more data points (Amro, Mundy & Kupczynski, 2015; Atchley, Wingenback, & Akers 2013; Cavanaugh & Jacquemin 2015). Like other studies in the literature, four groups of researchers used some form of course grade to measure student course outcomes (Amro, Mundy & Kupczynski, 2015; Atchley, Wingenback, & Akers 2013; Cavanaugh & Jacquemin 2015; Cooper 2001). The remaining four studies used exam grades (Ashby, Sadera, & McNary, 2011; Gulacar, Damkaci, & Bowman 2013; Jorczak & Dupuis 2014) or pre and posttest scores (Smeal et al, 2013) to measure student outcomes. These
research articles used a variety of sample sizes and course outcome measurements but determined that student outcomes were higher in online class modalities than in face-to-face classes.
<table>
<thead>
<tr>
<th>Study</th>
<th>Sample Size</th>
<th>Outcome Variable</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amro, Mundy &amp; Kupeczynski, 2015</td>
<td>22,219</td>
<td>Course grade</td>
<td>Scores significantly higher in online classes</td>
</tr>
<tr>
<td>Aly, 2013</td>
<td>307</td>
<td>Weekly assignments; major assignments; final exam grade; course grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Arias, Swinton &amp; Anderson, 2018</td>
<td>32</td>
<td>Pretest improvement; exam scores</td>
<td>Scores significantly higher in face-to-face classes</td>
</tr>
<tr>
<td>Ashby, Sadera, &amp; McNary, 2011</td>
<td>167</td>
<td>Unit tests; competency exam</td>
<td>Scores significantly higher in online classes</td>
</tr>
<tr>
<td>Atchley, Wingenback, &amp; Akers, 2013</td>
<td>5,477</td>
<td>Course letter grade</td>
<td>Scores significantly higher in online classes</td>
</tr>
<tr>
<td>Bunn, Fischer &amp; Treba, 2014</td>
<td>~100</td>
<td>Course Grade; GPA</td>
<td>Scores significantly higher in face-to-face classes</td>
</tr>
<tr>
<td>Cavanaugh &amp; Jacquemin, 2015</td>
<td>6,012</td>
<td>Course GPA</td>
<td>Scores significantly higher online, but no significant difference after controlling for covariates</td>
</tr>
<tr>
<td>Coates &amp; Humphreys, 2004</td>
<td>178</td>
<td>Scores on national exam</td>
<td>Scores significantly higher in face-to-face classes</td>
</tr>
<tr>
<td>Cooper, 2001</td>
<td>133</td>
<td>Course grades</td>
<td>Scores significantly higher in online classes</td>
</tr>
<tr>
<td>Dellana, Collins &amp; West 2000</td>
<td>199</td>
<td>Final course grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Euzent, Martin, Moskal &amp; Moskal, 2011</td>
<td>1,907</td>
<td>Final exam; course GPA</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Gutierrez &amp; Russo, 2005</td>
<td>~100</td>
<td>Course GPA; % of students with A grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Study</td>
<td>Sample Size</td>
<td>Outcome Variable</td>
<td>Results</td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>-------------</td>
<td>-----------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------</td>
</tr>
<tr>
<td>Gulacar, Damkaci, &amp; Bowman 2013</td>
<td>305</td>
<td>Exam scores, divides by question difficulty</td>
<td>Scores significantly higher in online classes</td>
</tr>
<tr>
<td>Hauck, 2006</td>
<td>288</td>
<td>Final course grades</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Johnson &amp; Palmer, 2015</td>
<td>317</td>
<td>Exam grades; final course grade</td>
<td>Scores significantly higher in face-to-face classes</td>
</tr>
<tr>
<td>Jorczak &amp; Dupuis 2014</td>
<td>104</td>
<td>Exam grades</td>
<td>Scores significantly higher in online classes</td>
</tr>
<tr>
<td>Kaupp 2012</td>
<td>4,500,000</td>
<td>Course letter grade</td>
<td>Scores significantly higher in face-to-face classes</td>
</tr>
<tr>
<td>LaMeres &amp; Plumb, 2014</td>
<td>~180</td>
<td>Homework; quizzes; exam grades; final course grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Lapsley, Kulik, Moody &amp; Arbaugh, 2008</td>
<td>63</td>
<td>Quiz grades; discussion grades; final project</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Larson &amp; Sung 2009</td>
<td>168</td>
<td>Exam scores; course grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Leasure, Davis, &amp; Theivon, 2000</td>
<td>66</td>
<td>Exam scores; final course grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Lim, Kim, Chen &amp; Ryder, 2008</td>
<td>153</td>
<td>Pre/post assessment</td>
<td>No significant difference</td>
</tr>
<tr>
<td>McDonnough, Roberts &amp; Hummel, 2014</td>
<td>81</td>
<td>Exam grades; project grades, final course grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>O’Brien, Hartshorne, Beattie &amp; Jordan, 2011</td>
<td>297</td>
<td>Course letter grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Reuter, 2009</td>
<td>97</td>
<td>Pre/post assessment; course grades; essay grades; assignment grades</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Rivera &amp; Rice, 2002</td>
<td>~140</td>
<td>Exam scores</td>
<td>No significant difference</td>
</tr>
</tbody>
</table>
### Table 1

<table>
<thead>
<tr>
<th>Study</th>
<th>Sample Size</th>
<th>Outcome Variable</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sussman &amp; Dutter, 2010</td>
<td>353</td>
<td>Paper grade; final course grades</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Thrasher, Coleman, &amp; Atkinson, 2012</td>
<td>878</td>
<td>Project grades</td>
<td>Mixed; some projects higher online, others higher face-to-face</td>
</tr>
<tr>
<td>Tseng &amp; Walsh, 2016</td>
<td>26</td>
<td>Course grade</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Verhoeven &amp; Wakeling, 2011</td>
<td>373</td>
<td>Success rates- a course letter grade of ABC</td>
<td>Scores significantly higher in face-to-face classes</td>
</tr>
<tr>
<td>Waschull, 2001</td>
<td>71</td>
<td>Exam scores; final exam score</td>
<td>No significant difference</td>
</tr>
<tr>
<td>Werhner, 2010</td>
<td>~300</td>
<td>Class exam scores</td>
<td>No significant difference</td>
</tr>
</tbody>
</table>

Overall, the results of this literature review of student outcomes in online versus face-to-face classes were mixed, as seen in Table 1. About half of the research suggested that there was no significant different among groups, while six articles suggested higher outcomes for face-to-face students, and eight indicated higher outcomes for online students. These results do not suggest one conclusive result for online course outcomes. The sample size for articles in this study was small, with only a few larger scale studies. While important to understand the overall impact of class modality on course outcomes that these articles provide, Rovai (2003) argues that student grades and persistence are complex subjects that are comprised of a complicated system of internal and external
factors. The next section of this literature review will focus on how the current literature has examined these characteristics and accounted for them in understanding student course outcomes.

**Studies that Account for Student Characteristics and Other Variables**

Of the 41 studies in the literature review, only 23 addressed or controlled for student characteristics or other factors related to student performance in their courses. There were 17 discrete characteristics examined in one or more studies, with the most popular being gender (19 studies), age (16 studies), and race (12 studies). Other characteristics referenced in more than one study included student GPA, number of previous credits taken, student major, ACT or SAT scores, previous online experience, and employment status. Characteristics that were only referenced once were full-time or part-time enrollment status, student year in school, Pell grant eligibility, first generation college students status, marital status, if students were repeating the class, student grade in the prerequisite class, and computer skills. Results from these 23 studies are summarized in table 2.

These characteristics align with the four categories listed in Rovai’s (2003) model of persistence: student characteristics, student skills, external factors, and internal factors. Student characteristics were most common including race, gender, age, ACT or SAT scores, etc. Student skills were less common but were measured in some instances by a computer skills score, grade in a prerequisite class, and previous online experience. External factors included marital status and employment, while internal factors included major, number of credits taken previously, full-time or part-time enrollment status, and
GPA. No one study captured all four of these characteristics, but each of Rovai’s categories was represented several times in these 23 studies that explored how student demographics and other factors contributed to student success.
Table 2

*A Summary of Literature Review Studies that Control for Student Characteristics*

<table>
<thead>
<tr>
<th>Study</th>
<th>Student characteristics</th>
<th>Student skills prior to enrollment</th>
<th>Internal Factors</th>
<th>External Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gender</td>
<td>Race</td>
<td>Age</td>
<td>SAT/ACT Scores</td>
</tr>
<tr>
<td>Arias, Swinton &amp; Anderson, 2018</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Amro, Mundy &amp; Kupczynski, 2015</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Ashby, Sadera, &amp; McNary, 2011</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Bunn, Fischer &amp; Treba, 2014</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cavanaugh &amp; Jacquemin, 2015</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Cooper, 2001</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Study</td>
<td>Gender</td>
<td>Race</td>
<td>Age</td>
<td>SAT/ACT Scores</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>--------</td>
<td>------</td>
<td>-----</td>
<td>----------------</td>
</tr>
<tr>
<td>Dellana, Collins &amp; West, 2000</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Dotterweich &amp; Rochelle 2012</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Euzent, Martin, Moskal &amp; Moskal 2011</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Gregory, 2016</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Johnson &amp; Palmer, 2015</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Kaupp, 2012</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Koch, 2005a</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Koch, 2005b</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Study</td>
<td>Gender</td>
<td>Race</td>
<td>Age</td>
<td>SAT/ACT Scores</td>
</tr>
<tr>
<td>---------------------------------------------------</td>
<td>--------</td>
<td>------</td>
<td>-----</td>
<td>----------------</td>
</tr>
<tr>
<td>Kupczynski, Brown, Holland &amp; Uriegas, 2014</td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>LaMeres &amp; Plumb, 2014</td>
<td></td>
<td>X</td>
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<tr>
<td>Lapsley, Kulik, Moody &amp; Arbaugh, 2008</td>
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<tr>
<td>Larson &amp; Sung, 2009</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Leasure, Davis, &amp; Theivon, 2000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reuter, 2009</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Verhoeven &amp; Wakeling 2011</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Waschull, 2001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Werhner, 2010</td>
<td>Gender</td>
<td>Race</td>
<td>Age</td>
<td>SAT/ACT Scores</td>
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<td>---------------</td>
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</tr>
<tr>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Studies with this Characteristic</td>
<td>19</td>
<td>12</td>
<td>16</td>
<td>3</td>
</tr>
</tbody>
</table>
Student Characteristics Prior to Entering the University

Student characteristics were the most common factor included in the studies in this literature review, with 21 of the 23 studies controlling for student demographic and other factors, including one or more student characteristics prior to entering the university. These included race, gender, age, SAT and ACT scores, and first-generation student status. Seven of these studies only examined student characteristics, and not any of Rovai’s other categories. In three of these cases, age was significantly different among groups, but was not a significant predictor of success rate (Ashby, Sadera, & McNary 2011; Larson & Sung 2009; Reuter, 2009). Two different large-scale studies examined student outcomes after controlling for gender, race, and age. In the first study, the researchers found that after controlling for gender, race, and age in 22,000 college algebra students, online students had significantly higher course grades than did face-to-face students (Amro, Mundy & Kupczynski, 2015). In contrast, in the second study of 4.5 million California community college students, face-to-face students had significantly higher grades after controlling for gender, race, and age (Kaupp, 2012). Although frequently studied in the articles included in this literature review, there was no conclusive evidence of the impact of student characteristics on course outcomes in online and face-to-face classes. The second category of characteristics was student skill sets.

Student Skills Prior to Entering the University

Six of the twenty-three studies looked specifically at student skills before taking the class in question. These skills included a measure of computer literacy, previous online course experience, and a grade in a prerequisite course. Of these measures,
computer skills were only measured in one study, and the author found that after controlling for this and other characteristics, there was no significant different between groups (Dellana, Collins & West, 2000). Additionally, only one study examined student grades in a prerequisite class, and found that for both strong and weak students coming into the higher-level course, success rates in the course, as measured by an earned A, B, or C grade in the class, were significantly higher for face-to-face students (Verhoeven & Wakeling, 2011). The final characteristic of previous online course experience was studied in four cases. Three of these studies attempted to define the characteristics of students who chose to enroll in an online class rather than specifically controlling for these characteristics in examining course outcomes. In all of these cases, previous student online class experience had a positive impact on student success rates (Dotterweich & Rochelle, 2012; Koch, 2005a, 2005b). A final study also controlled for previous online experience and found no significant difference on course assessments among groups (Reuter, 2009). These studies suggest that student skills do have an impact on success rates in online classes, and that controlling for these skill sets can impact statistical results. In addition to student characteristics and skills prior to entering college, there are other factors that influence student performance in higher education.

**Internal Factors that Impact Student Outcomes**

Of the 23 articles that examined outcomes together with student characteristics, 14 looked at one or more internal factor related to the student’s university experience. These factors included the academic performance indicators (grade point average, number of credits completed, and if the student was repeating a particular class) and goal
commitment factors (a declared major, and full-time or part-time enrollment status) suggested by Rovai’s (2003) model. Rovai’s third factor of social integration was not measured by any of the research articles in this literature review. Results in these 14 studies indicated no significant difference in outcomes six times and were used as a measure of student enrollment trends by demographics and other characteristics with no specific course outcomes in five studies. Only three studies indicated a significant difference among groups, with higher outcomes in face-to-face students in all cases.

Academic performance factors included grade point average; number of credits completed, or year in school; and if the student was repeating the class. In one study that controlled for GPA and credit hours, among other characteristics, the researchers found a significantly higher outcome for online students until they controlled for student characteristics, when there was no significant difference in outcomes (Cavanaugh & Jacquemin, 2015). In another study that examined the GPA of students enrolled in online and face-to-face classes, the authors found that there was no significant difference in academic preparation among groups, so this factor did not affect course outcomes (LaMeres & Plumb, 2014). Among the articles that specifically examined student academic preparation, academic performance was sometimes significantly different among groups (Euzent, Martin, Moskal & Moskal, 2011; Lapsley, Kulik, Moody & Arbaugh, 2008), but at other times was not statistically different (Dellana, Collins & West 2000; Leasure, Davis, & Theivon, 2000).

Only five of the 14 articles that explored internal factors focused on student goal commitment as measured by a declared major, or by full-time or part-time enrollment
status. Interestingly, three of these five articles showed a significant result with higher scores for face-to-face students (Arias, Swinton & Anderson, 2018; Bunn, Fischer & Treba, 2014; Johnson & Palmer, 2015). However, of these three articles, both Johnson and Palmer (2015), and Arias, Swinton and Anderson (2018) found that there was no correlation between goal commitment characteristics and student enrollment patterns. In these studies, student goal commitment was not considered a significant factor in determining student course outcomes. Other research indicates that after controlling for goal commitment characteristics, there is no significant difference in course outcomes among groups (Cavanaugh & Jacquemin 2015). Overall, internal factors of academic performance and goal commitment had mixed outcomes. The final category of student characteristics is factors external to the student university experience.

**External Factors that Influence Student Outcomes**

Only four articles specifically examined external factors related to student success rates in online classes. This research looked at Pell grant eligibility as a measure of financial status, as well as marital status, and employment in a total of four studies. The first of these studies did not compare course outcomes by controlling for these characteristics but did find that students who were non-Pell grant eligible and married were more likely to succeed in online classes (Gregory, 2016). This was the only study to examine these two characteristics. Three studies controlled for student employment as one of several factors in their research, and two found that after controlling for these characteristics, there was no significant difference among groups (Dellana, Collins & West, 2000; Euzent, Martin, Moskal & Moskal, 2011). In contrast, one other study found
that there was a significant difference between class modality on student employment, with more employed students in online classes. Online students were more likely to earn an A than their face-to-face peers (Cooper, 2001).

**Summary of the Impact of Student Characteristics on Course Outcomes**

While more than half of the research studies included in this literature review attempted to control for some student characteristics, there was little definitive evidence of the impact these characteristics had on course outcomes. Studies controlled for one to eight characteristics, with 13 studies only controlling for between one and three characteristics. Studies that focused solely on student characteristics prior to starting college, found that either race, gender, or age were not significant predictors of course outcomes, or different studies had contrasting outcomes of how these characteristics impacted outcomes. Studies focused on student academic skills were less common but did suggest that characteristics such as computer literacy and previous online experience were important to understanding course outcomes. Internal factors such as academic performance and student goal commitment also provided mixed results, with some suggesting that there is no significant difference among groups, and others finding that after controlling for grades and enrollment types, there were higher scores in either face-to-face or online classes. The final category of external factors, such as marital status and employment status also found mixed results in small scale-studies that did not definitively state the importance of these factors in assessing student outcomes. Understanding the complex relationship between all four categories of student characteristics and systematically studying them in a large-scale study is one way to
account for the selection bias inherent in student self-selection into different class modalities.

**Importance of Examining Covariates to Account for Selection Bias**

It is important to understand the impact of student characteristics, demographics, and other factors on course outcomes because students self-enroll into face-to-face, online, and hybrid class modalities, making these studies observational studies. These studies are not able to draw strong statistical conclusions about causality because the researchers have no way to control for selection bias among the different class groups. Some researchers specifically acknowledge the bias of self-selection into different class modalities (Thrasher, Coleman, & Atkinson, 2012; Werhner, 2010). Despite this, there is a limited effort to control for this selection bias, since only 23 of the 41 studies in this literature review attempted some method of controlling for student characteristics. Additionally, in one study in this literature review that controlled for selection bias through random selection, they accounted for only seven characteristics when assigning groups (Arias, Swinton & Anderson, 2018).

Coates and Humphreys (2004) suggest that “self-selection into online classes is an important issue in the assessment of the effectiveness of online education in economics. Failure to account for the effects of selection leads to biased and inconsistent coefficient estimates” (p. 545). Even among those studies that do control for student characteristics, most only examine a few characteristics, with only ten of 41 studies in this literature review controlling for more than three student characteristics or other factors. Given that Rovai (2003) argues that student performance and persistence is a complex relationship
between student characteristics, skills, and internal and external factors to their college education, the literature in this study shows a significant gap in understanding how these factors collectively impact online course outcomes. Propensity score analysis is one statistical method that allows for evaluation of the effect of multiple confounding covariates introduced by student self-selecting into online or face-to-face classes on statistical outcomes.

**The Value of Propensity Score Analysis**

Propensity score analyses (PSA) are a set of statistical methods that can be used on observational data. They can be particularly helpful when a randomize control trial is not feasible in circumstances like education when student self-select into different class types, and can introduce selection bias (Rubin, 1997). Rosenbaum and Rubin (1983) first introduced the idea of this statistical method as a way to estimate causal effects from observational data.

When a random control study is not ethical or practical, propensity score analysis offers a method for controlling for selection bias in an attempt to estimate causality (Guo & Fraser, 2015). Guo and Fraser (2015) identify several different methods for PSA, including greedy matching, the Mahalanobis distance metric, optimal matching, and weighted PSA. By using a determined list of confounding covariates, PSA allows a statistical match between an individual in the treatment group and one or more individuals in the control group based on personal characteristics. These methods may reveal imbalance between treatment and control groups, and allow for an estimate of treatment effect after correcting for this imbalance. None of the studies included in the
original literature review for this dissertation addressed student performance in online courses using this robust statistical method.

With this gap in the literature in mind, the researcher performed a new search specifically examining studies that control for selection bias in online course outcomes in robust propensity score studies, and only found six studies that did so.

**Propensity Score Studies and Online Course Outcomes.** These six papers found the same consistent result in online course outcomes: online students performed worse than their face-to-face counterparts did. Xu and Jaggars (2011a, 2011b, 2013, 2014) are the most prolific researchers in this field of study and have examined online course outcomes in the community college system. Wladis, Conway, and Hachey (2015) also examined student outcomes at community colleges. The final study by Smith (2017) examined student online course outcomes at a state four-year college system by controlling for many demographic, academic, and institutional factors.

Each of these six studies examined multiple student demographic, academic, and personal factors to understand their impact on course outcomes. These rigorous studies all found that after controlling for selection bias, there was a negative effect of online course enrollment on student outcomes. Students in online classes earned lower course grades (Smith, 2017; Xu and Jaggars, 2011a, 2011b, 2013) than their face-to-face peers. They also withdrew at higher rates than on-campus students did (Smith, 2017; Wladis, Conway, and Hachey, 2015; Xu and Jaggars, 2011a, 2011b, 2013, 2014).

The importance of these studies is that in all cases, researchers found significant negative effect of online course enrollment after controlling for a wide variety of student
characteristics as covariates. Research in the previous literature review found that more than half of the research studies indicated no significant difference between groups, which is a marked contrast with these more rigorous studies that control for many student factors. The small number of studies that control for student factors indicates a need for more research in this area. Although race is an important demographic factor examined in many studies, another important gap in the literature up to this point is the lack of research that specifically focuses on course outcomes at Hispanic-Serving Institutions.

**Online Course Outcomes at Hispanic Serving Institutions**

There is a paucity of literature related to online course outcomes at Hispanic-Serving Institutions. In this literature review, no studies examined these outcomes, so the researcher conducted a hand search for online course outcomes and Hispanic-Serving institutions. This hand search yielded only three results, and these articles vary widely from the selection criteria for the previous literature review. One study examined graduate student perceptions of online courses at an HSI rather than student course outcomes (Lu & Cavazos Vela, 2015). Another study found a significant difference in online and face-to-face course outcomes at an HSI community college, with better outcomes for online students than for face-to-face students (Wladis, Conway, & Hachey, 2015). The third study controlled for only age and ethnicity but found that these characteristics were contributing factors to student success in online anatomy and physiology courses at an HSI in Texas (Camara, 2016). While interesting, these results are limited to a few studies, some of which are not directly related to undergraduate education at a four-year institution, explore qualitative perceptions, or control for only a
few covariates in determining student outcomes. This lack of information suggests a further need for understanding online course outcomes at a four-year HSI, particularly through a large-scale, comprehensive study that controls for a variety of characteristics in order to understand student academic performance.

**Summary and Conclusions**

Student integration theory indicates that student demographic, academic, and institutional factors all contribute to course outcomes. Rovai (2003) suggests using a modified version of Tinto’s (1993) model of student persistence that examines student characteristics prior to attending college, student skills prior to attending college, and internal and external characteristics that impact student performance while enrolled at the university. Incorporating the characteristics presented by this model into research related to online course outcomes will help to control for selection bias and to better understand the complex relationship between student characteristics and course performance.

To this point in time, there is a large body of literature related to outcomes in online and face-to-face classes, with mixed results of the impact of online classes on student course grades. These studies largely do not control for the selection bias inherent in student self-enrollment in different course modalities. Those studies in this literature review that address selection bias typically examined only a few student characteristics, with no studies that examine student characteristics in all four of Rovai’s categories. A robust propensity score statistical model could provide possible outcomes, but there has been limited research using this method in the past. An expanded literature search revealed seven studies that have attempted to control for this selection bias on an
institutional scale, but none have been completed at a four-year Hispanic serving undergraduate university.

As this literature review shows, there is a need for a large-scale study at a four-year Hispanic-Serving Institution that systematically explores Rovai (2003) and Tinto’s (1993) student integration theory in an online context. This current study will attempt to control for student characteristics as covariates in understanding student online course outcomes at an HSI through the lens of student integration theory in order to fill that gap.
Chapter 3 – Methods

As shown in the literature review in the previous chapter, student demographic and other academic characteristics can have an impact on course outcomes. Understanding this impact is particularly important in educational settings where the student self-enrollment into particular courses and course modalities can introduce selection bias that can affect our understanding of course outcomes (Coates and Humphreys, 2004). The literature review showed that only six previous studies have systematically controlled for a wide variety of student characteristics through propensity score analysis, and none of these studies specifically focused on online course outcomes at a four-year Hispanic-Serving Institution (Smith, 2017; Wladis, Conway, and Hachey, 2015; Xu and Jaggars 2011a, 2011b, 2013, 2014).

To fill this gap, the current research project explores the research questions: To what extent does enrollment in a fully online class as compared to face-to-face classes affect course grades for students who complete the course? In addition, to what extent does enrollment in a fully online course as compared to face-to-face classes affect course withdrawal rates?

This study uses propensity scores as a measure of student probability of being in the treatment (online) group given a set of controlled covariates. The researcher tested
three propensity score models, using a sensitivity analysis to choose the most robust result given the results from the data collection process.

**Setting**

This study used an observational approach to examine data from an urban, four-year, Hispanic-Serving Institution to determine the relationship between student characteristics and success in online classes. The setting for this study is Russell University (pseudonym), a large, public university located on an urban campus in a downtown metropolitan area in the mountain west. This pseudonym was selected based on the name of one of the original founders of the town where this university is located. Demographics at this institution include many first-generation college students, students of color, and part-time students. Detailed demographics of this data set are included later in this chapter. In 2019, the institution earned the Hispanic-Serving Institution designation by enrolling and retaining a threshold of at least 25% Latino students (Watson, 2019).

According to the Associate Vice President of Online Learning at Russell University, during the 2018-19 school year, 24% of course enrollments at this institution were in online classes, showing a continued trend of increased course enrollment since online classes were first offered at the institution. The Associate Vice President added that as of fall 2018, 38.9% of students enrolled in one or more online classes (AVP, personal communication, July 18, 2019). The university offers a broad range of online courses and programs in both undergraduate and graduate programs. These offerings include over 100 majors, eight graduate programs, and 34 certificate programs. For this
study, any course taught at the undergraduate level in both online and face-to-face formats was included in the data set.

**Ethical Considerations**

Because data were collected anonymously through the university system, the ethical considerations of this study are limited. IRB exempt status was issued by both the University of Denver and Russell University. In this data collection process, all information provided by Russell University were de-identified using a proxy student ID. At no point did the researcher have the ability to connect data to specific student identities. Additionally, the researcher has used a pseudonym for the data collection site. After data collection, the researcher is safeguarding data on a password-protected computer to ensure that no others can access it.

**The Researcher in this Context**

The researcher in this study has six years of experience teaching online classes at Russell University. This work experience has an impact on the researcher’s beliefs related to online course outcomes, and this statement intends to clarify this bias. The topic of student outcomes in online course is of interest to the researcher for several reasons. As a faculty member who teaches online classes, the researcher felt that there were a diversity of reasons that students might choose to enroll in an online class rather than a face-to-face course. Many of these reasons, such as family and work obligations, also had an impact on student course grades and withdrawal rates. Quantifying these reasons and controlling for them in a rigorous statistical examination of student course outcomes at the university level founds the basis for this study. While the researcher is a
member of the university community at Russell, they have chosen a large, de-identified, university-wide data set and a statistical method that will allow them to address research questions objectively.

**Research Design**

*Research Questions*

This study examines the effect of enrollment in online classes as compared to face-to-face classes on student outcomes. It specifically examines the extent to which enrollment in online courses affects the academic achievement of students at Russell University while controlling for a variety of confounding covariates. The research questions for this study are:

To what extent does enrollment in a fully online class as compared to face-to-face classes affect course grades for students who complete the course?

To what extent does enrollment in a fully online course as compared to face-to-face classes affect course withdrawal rates?

*Treatment Variable*

The independent variable in this study is course modality (online or face-to-face). Many students in the data set enrolled in a combination of online and face-to-face courses. For the purposes of this study, students who completed 75% or more of their courses online were included in the online treatment group. Students who completed 75% or more of their courses face-to-face were included in the control group. All other students were eliminated from the study. Results from course modalities other than online
and face-to-face courses were excluded from the study; these included blended or hybrid
courses, distance courses taught at satellite campuses, and self-paced online courses.

**Outcome Variables**

The dependent variable for the first research question is course outcome, as
measured by student grade in the course (A, B, C, D, and F). All courses taught at Russell
University use this grading method as a standard. Pass/Fail grading is an exception, and
must be requested by the student; this scoring is only allowed in elective courses that do
not count towards a major or minor, and no pass/fail grades appeared in the dataset for
this study.

**Student Grades.** In aggregating student data, the final measure of student grades
was an average GPA for all courses in which the student earned a letter grade. If the
student enrolled in five classes during the two year study period, the course grades for
those classes were averaged to produce a composite GPA for all coursework in which the
student completed the course and earned a letter grade.

In previous research there have been many methods of measuring student
outcomes, including grades on course projects or assessments (Hurlbut, 2018), and a pre-
test/post-test measure of improvement in the course (Arias, Swinton & Anderson, 2018).
The most common measure of student course outcomes has been some measure of course
grade, including the students’ final percentage grades in the course (Tseng & Walsh,
2016), and success rates measured as earning at least an A, B, or C grade in the course
(Verhoeven & Wakeling 2011). An average, or course GPA is a common method of
measuring student performance as seen in other research (Euzent, Martin, Moskal &
Moskal, 2011; Gutierrez & Russo, 2005). While grades are only one measure of student success, they are used in many studies as a stand-in for student performance.

**Student Withdrawal Rates.** The dependent variable for the second research question is withdrawal rates in the courses included in this study. Students who withdraw from academic courses do not earn a course letter grade, and are assigned a grade of W for the course instead. Earning a W or a completing the course and earning a course letter grade was flagged as a dichotomous variable for each data point. When aggregating data for each student, I calculated the overall percent withdrawal rate by dividing the number of withdrawn courses by the total number of courses in which a student enrolled. This percentage withdrawal rate for all enrolled classes served as the measure for withdrawal rates for sub question B.

**Covariates**

The study also controlled for confounding covariates that may have introduced selection bias when students self-selected into different course types. These covariates included: student demographics, academic characteristics, and institutional factors. The factors selected for this study follow Smith’s (2017) model of Student Integration Theory (Rovai, 2003; Tinto, 1975, 1993). This model of student integration (Rovai, 2003) introduces student characteristics that fit into four different categories, and the researcher attempted to include factors from each of those four categories: (a) student characteristics; (b) student skills; (c) internal factors and (d) external factors.

It is difficult to track each of these student characteristics in a large institutional data set, but some of these data are available through institutional data collection. For
example, when enrolling at the university, students completed a demographic survey providing details about race, gender, and age. Additionally, the university tracks other data related to employment status and other personal characteristics. The sections that follow provide details about which specific factors the researcher included in the study and how they align with the student integration model (Rovai, 2003; Smith, 2017; Tinto, 1975, 1993).

**Student Characteristics.** These characteristics are student demographic and academic performance factors measured in an enrollment survey. Factors included from the demographic category are race, gender, age, first-generation student status, and veteran status. This study also controlled for zip code to understand student travel distance to campus. Academic performance factors related to performance prior to enrollment at the current institution are available through high school and transfer GPAs.

**Student Skills.** Student skills prior to enrollment are more difficult to estimate for purposes of this study. Rovai (2003) includes student academic skills prior to enrollment in this category, including computer literacy, information literacy, time management, reading and writing skills, and computer skills. The researcher was not able to include many of these items as covariates in the study, as Russell University does not track data related to computer skills, information literacy, or time management. The one variable available from the institution that fits within this category is a proxy measure for reading and writing skills. The institution collects scores on SAT and ACT college entrance exams, which are intended as a measure of college readiness. Students at Russell University can apply with scores from either exam, which provides a variety of results for
this measure. However, missingness for SAT scores was 95%, and this variable was eliminated from the study, while retaining ACT scores as a proxy for reading and writing skills.

**Internal Factors.** Rovai (2003) defines internal factors as the largest category of factors that influence student persistence. This category includes 22 different factors that relate to the student college experience, including measures of academic performance, including current GPA and rate of attendance. Other measures of internal factors in Rovai’s model include academic integration. Students’ choice to commit to academic goals leading to graduation (goal commitment), or access to services like advising or student organizations form part of the academic integration at the institution.

In order to assess the internal factors enumerated by Rovai (2003), this study measures academic performance in two ways: first, by current grade point average as of the most recent semester of enrollment, and second, by number of credits completed at the institution during the most recent semester of enrollment. Students listing a declared major stood as a measure of student goal commitment, as this implies a commitment to complete an academic goal leading to graduation. This was a dichotomous variable indicating if the student had declared a major in the most recent semester of enrollment, not a reflection of which major students had declared. Rovai (2003) also lists institutional commitment as a factor influencing student success. An institutional commitment indicates a student sense of commitment to the university. This study measures this sense of commitment with a proxy variable of enrollment status. This assumes that students enrolled full-time (12 or more credits each semester) are more committed to the
institution than those who are enrolled part-time (fewer than 12 credits a semester). This assumption is consistent with Rovai’s suggestion that part-time students need additional supports towards persistence and graduation than do full-time students (2003). For this study, as students may have been enrolled full-time in one term, and part-time in another term, an aggregate variable calculated the number of full time terms and divided by the total number of terms enrolled. These calculations resulted in a continuous variable marking the percentage of full-time terms.

Rovai (2003) lists other internal factors related to student performance, including (a) social integration with peers; (b) identification with the school or feeling a sense of belonging at the institution; (c) program fit, which is how well a student integrates with their major or academic program; (d) pedagogical preferences such as learning style, and (e) student feeling of satisfaction at the institution are difficult to measure with an institutional data set, and were excluded from this study.

**External Factors.** Student characteristics external to the university experience can be measured in several ways. First, student marital status is a way to measure for family responsibilities, although it does not capture the number of dependents in that family structure, or the external support that a family system may or may not provide. In this study, marital status was included based on student status in the most recent term of enrollment. Hours of employment will be measured by full-time employment status, part-time employment status or no current employment in student self-reports to the institution.
Financial circumstances such as income and financial support from parents or others are not available as a direct measure on the institutional data set, but one stand-in for this information is available through financial aid records. FAFSA data indicates both Pell Grant eligibility and student income brackets. Students with fewer financial resources may be eligible for a Pell Grant, while those who are more financially stable would not be eligible for this type of financial aid. This Pell Grant data can be confirmed by income bracket information. One limitation of this measure is that the group of students who were not eligible for Pell Grants includes both students who applied for FAFSA and were not eligible, and those who did not apply, which skews the effect of these data. Since data related to income are only collected from those students who apply for financial aid, this information is not available for students who chose not to apply for FAFSA. All covariates included in this study are summarized in Table 3.
Table 3

*Covariates included in the study with their variable type.*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable type</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Student Characteristics Prior to Enrollment</strong></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td>Categorical</td>
</tr>
<tr>
<td>Gender</td>
<td>Dichotomous</td>
</tr>
<tr>
<td>Age</td>
<td>Continuous</td>
</tr>
<tr>
<td>High school GPA</td>
<td>Continuous</td>
</tr>
<tr>
<td>Transfer GPA</td>
<td>Continuous</td>
</tr>
<tr>
<td>Veteran status</td>
<td>Continuous</td>
</tr>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt; generation student status</td>
<td>Continuous</td>
</tr>
<tr>
<td>Zip code</td>
<td>Categorical</td>
</tr>
<tr>
<td><strong>Student Skills Prior to Enrollment</strong></td>
<td></td>
</tr>
<tr>
<td>ACT Scores</td>
<td>Continuous</td>
</tr>
<tr>
<td><strong>Internal Institutional Factors</strong></td>
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</tr>
<tr>
<td>Current GPA</td>
<td>Continuous</td>
</tr>
<tr>
<td>Declared major (Yes or No)</td>
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</tr>
<tr>
<td>Number of credits completed</td>
<td>Continuous</td>
</tr>
<tr>
<td>Student enrollment status</td>
<td>Continuous</td>
</tr>
<tr>
<td><strong>External Student Factors</strong></td>
<td></td>
</tr>
<tr>
<td>Marital status</td>
<td>Continuous</td>
</tr>
<tr>
<td>Employment status</td>
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</tr>
<tr>
<td>Income bracket</td>
<td>Continuous</td>
</tr>
<tr>
<td>Pell grant eligibility</td>
<td>Continuous</td>
</tr>
</tbody>
</table>

**Data Collection Procedures**

The HSI business intelligence office released de-identified secondary data related to the specific students for this study for the past academic two years, AY 2017-2018 and AY 2018-2019. The data included all students who enrolled in an either an Online or Face-to-Face section of a course that is offered in both formats. The institution designates
hybrid courses as their own course type, and these courses were eliminated from the study. The number of unique course enrollments in the original sample was 157,161.

Data included de-identified demographic and course outcome data from any course enrollment for any student enrolled in any undergraduate course that offered both online and face-to-face sections. A comparison of demographic data for these students allows this study to control for differences in race, gender, academic performance, and other personal characteristics. Data for this study are related to undergraduate students enrolled in undergraduate courses offered in both fully online and fully face-to-face formats. Other data were eliminated from this study using the procedures outlined below. The charts outlined below provide overall demographic data for the sample:

- Gender with 52.70% females in the sample, and 47.3% males (figure 3)
- Race or ethnicity. White students comprise 46.10% of the sample, with Hispanic students making up 33.40% of the sample (figure 4)
- Declared or undeclared major. In this sample, 88.20% of students had a declared major while 11.80% were undeclared (figure 5)
- First-generation student status. The sample at Russell University is comprised of 60.00% first generation college students and 40.00% not first-generation college students (figure 6)
- Student transfer status. Transfer students comprise 22.30% of the sample at Russell University, with non-transfer students making up 77.70% of all students (figure 7)
- Age at first enrollment at Russell University. The most frequent age was 18 years old at first enrollment at Russell University, comprising 52.8% of the sample (figure 8).
- Veteran status for students at Russell University. 98.1% of students were not veterans (figure 9).
- Pell Grant eligibility for students at Russell University. These data show that 55.20% of students were not Pell-eligible or did not apply for Pell-grants, while 44.80% were Pell-eligible (figure 10).

*Figure 3.* A bar chart of participant sex for the data set from Russell University.
Figure 4. A bar chart showing the race or ethnicity breakdown for the sample at Russell University.

Figure 5. A bar chart showing student declared major status at Russell University.
Figure 6. A bar chart showing first generation student status at Russell University.

Figure 7. A bar chart showing transfer status for Russell University.
Figure 8. Chart showing age at first registration of students at Russell University.

Figure 9. A bar chart showing veteran status for Russell University.
Figure 10. Chart showing Pell Grant eligibility at Russell University.

The researcher took steps to review data before analysis to ensure that the data set only contained information related to undergraduate, degree-seeking students taking an undergraduate course fully online versus undergraduate, degree-seeking students taking the same undergraduate course in a fully face-to-face format. These steps are modified from the steps outlined in Smith (2017) in similar research. First, the researcher checked data from the institution to ensure that only eligible online and hybrid courses were included in the data set. These data also only included degree-seeking, undergraduate students. The original data included 157,161 unique course enrollments.

To avoid a circumstance where one student was enrolled in both online and face-to-face classes, and thus appear in both the treatment and control groups, the researcher conducted an aggregation process to define one data point for each student. This during this process, the researcher calculated an average GPA for all courses in which the students earned a course grade, and calculated withdrawal rates. The aggregated data
reduced 157,161 enrollments to aggregated information for 28,679 unique students in the study.

Next, the researcher identified students in the treatment and control groups for this study by designating the treatment group as those students who had enrolled in 75% or more online classes for the duration of the study. The control group contained those students who had enrolled in 75% or more face-to-face classes for the duration of the study period. All other students were eliminated from the study, resulting in 20,640 individuals in the study.

Finally, the researcher evaluated the remaining cases for missing data, which resulted in the elimination of one variable (SAT scores), and all other student cases where data were missing using a list wise case deletion method. The final number of cases included in the study was 7,765. See figure 11 for a summary of data aggregation.
Data Analysis Procedures

After data collection and data review, the researcher coded the data to assign students to two different treatment groups as a dichotomous variable. Students enrolled in 75% or more online courses (treatment) were coded as a one. Students enrolled in 75% or more face-to-face courses (control) were coded as a zero. Course grades were recorded as a continuous variable of the average GPA for all courses in which students earned a letter grade. Withdrawal rates were coded as continuous variable of the percent of courses.
withdrawn for each student. Each of the categorical and dichotomous covariates were also coded for analysis.

After coding the data, the researcher used the R statistical analysis package to conduct a propensity score analysis of the data. In order to determine the most robust model for this data set, the researcher tested three propensity score methods and evaluated them using a sensitivity analysis (Leite, 2017; Rosenbaum, 2002) to determine their robustness before selecting a final evaluation method. Propensity score analysis (PSA) is a statistical method that allows for evaluation of treatment effect on observational data. When a random control study is not practical, propensity score analysis offers a method for controlling for selection bias (Guo & Fraser, 2015). This statistical methodology can help counter the selection bias introduced when students with different personal characteristics self-select into different course types, and can allow for an estimate of treatment effect after controlling for confounding covariates. Guo and Fraser (2015) identify several different methods for PSA, including greedy matching, optimal matching, and weighted PSA. Each method requires the fulfillment of different statistical assumptions from the data, and allows for different statistical tests to evaluate treatment effect. In order to select the most appropriate model for the data in this study, the researcher collected the data, and then evaluated which PSA method would be the best fit based on the assumptions met by the actual data set. At this point, the researcher will conducted a sensitivity analysis (Leite, 2017) to determine the robustness of each PSA model, and the fit to the data in the current dataset. After selecting the best statistical
model for each research question, the researcher will estimated treatment effect using a two-sample $t$-test.

Summary

The purpose of this study is to examine the effect of online course instructional methods on course outcomes of students at a large, public, four-year, Hispanic-Serving Institution in Urban population in a state in the mountain west. Data for this study come from a dataset at this institution that includes students enrolled in courses offered in both online and face-to-face modalities over a two-year period starting in fall 2017 to spring 2019. The treatment variable for this study is course modality, or if a student is enrolled in an online or a face-to-face course. Outcome variables for this study include measures of course grade through course letter grade earned in the course as well as course withdrawal rates. In order to control for selection bias inherent in the self-enrollment process in these classes, this study will include covariates that follow Rovai’s (2003) model for student persistence in online classes in four categories: student characteristics before starting college, student skills, internal factors, and external factors related to the academic experience. The researcher will test multiple propensity score models to find the model that is the best fit given the actual data in the dataset. They will then conduct a sensitivity analysis to determine the most robust model before determining the effect of treatment on student course outcomes.
Chapter 4- Results

This chapter will discuss results from the current study. First, this chapter will include a summary of data collection and analysis procedures. Second, the author will provide baseline data for effect of treatment and balance of the sample in treatment and control groups. Third, the chapter will focus on validity and sensitivity of three different propensity score methods evaluated for the study: near-neighbor matching, Mahalanobis’ distance metric, and optimal matching. This study evaluated all three PSA methods, and the researcher selected the near-neighbor 1:2 matching method as the best fit for the current data in terms of validity and sensitivity. Finally, the chapter will conclude by summarizing overall results of the study using the near-neighbor 1:2 matching technique with a two-sample t-test to evaluate student grades and course withdrawal rates.

Summary of Data Collection & Analysis

Data for the study were collected from Russell University for each student enrolled a class offered in both online and face-to-face formats during the 2017-2018 and 2018-2019 academic years. The researcher collected data for 15 different covariates as well as student course grades and withdrawal rates. Many students participated in both online and face-to-face course offerings. To avoid placing the same student in both the treatment (online) and control (face-to-face) groups, the researcher aggregated the data for each individual into one data point. Students who enrolled in 75% or more online.
classes were included in the treatment group. Students who enrolled in 75% or more face-to-face classes acted as the control group. All other students were eliminated from the study, leaving the data set with \( n = 7,765 \).

These data underwent a propensity score analysis using three different methods to determine the most robust model for the data. First, the researcher used a greedy matching technique with 1:1 and 1:2 ratios with a two-sample \( t \)-test to compare results for the two outcome variables: average student GPA, and student withdrawal rates. Second, the researcher used a Mahalanobis distance matching method, and finally used optimal matching with 1:1 and 1:3 ratios, both with a two sample \( t \)-test to compare results for the outcome variables. After completing these matching methods, the researcher used a sensitivity analysis (Rosenbaum, 2002), to determine how robust each method was to hidden bias from possible missing covariates in the statistical model. These sensitivity statistics were important in determining how robust the results were for each statistical test. After conducting these three propensity score tests, and a sensitivity analysis, the researcher examined the quality of balance between treatment and control groups, the number of cases that were included in the model, and the degree of sensitivity to hidden bias in determining which of the models would be used for final analysis in this study.

Baseline for Effect of Enrollment

**R1: Student Course Grades**

The first research question in this study is: To what extent does enrollment in a fully online class as compared to face-to-face classes affect course grades for undergraduate students who complete the course? In order to answer this question at a
baseline level, the researcher completed initial statistical testing to determine a baseline for the effect of enrollment in an online class on student course grades using a two-sample $t$-test. This baseline measurement took place before completing propensity score matching to balance the sample based on the covariates in the study.

The results from this two-sample $t$-test indicate that online students have a higher course GPA ($m = 2.55$) at a statistically significant level, than did face-to-face students ($m = 2.34$), $t (7763) = -5.80, p < .001$). See figure 1. The baseline data for the study suggest enrollment in a fully online class as compared to a face-to-face class has a statistically significant effect of course enrollment, with an average GPA in online classes 0.21 points higher than for face-to-face students prior to statistical matching to balance out online and face-to-face groups. See figure 12.

![Boxplot of student GPA based on course enrollment at Russell University.](image)

*Figure 12.* Boxplot of student GPA based on course enrollment at Russell University.
R2: Student Withdrawal Rates

The researcher also tested results for student withdrawal rates to answer research question 2: To what extent does enrollment in a fully online course as compared to face-to-face classes affect course withdrawal rates for undergraduate students?

Results of a two-sample t-test indicate that in the initial, unbalanced sample, there is no statistically significant difference between the withdrawal rates of online and face-to-face students $t(7763) = -1.07, \ p = 0.28)$. See figure 2. These data suggest that prior to propensity score matching, enrollment in a fully online class as compared to a face-to-face class does not affect course withdrawal rates for undergraduate students. See figure 13.

Figure 13. Boxplot of student withdrawal rates based on course enrollment at Russell University.
**Testing for Balance between Online and Face-to-face Groups**

The researcher performed a Chi Square test of these initial data to examine the relationship between covariates and the course grades and withdrawal rates. The association between these variables was statistically significant, $\chi^2 (15) = 1407, p < .001$. This statistically significant result indicates that there is an association between course grades, and one or more of the covariates included in the study. There were 15 covariates included in this study, and these results indicate that one or more those covariates are significantly influencing the enrollment pattern in online or face-to-face classes, the selection variable in this study. The covariates included in this study were: sex, race, age, a declared major, veteran status, first-generation student status, number of credits completed, current GPA, percent of semesters with full-time enrollment, ACT scores, high school GPA, transfer status, Pell grant eligibility, income, and zip code. Of these 15 covariates in the sample, eight had a significant impact on the imbalance between enrollment groups prior to matching. These eight covariates were: the maximum number of credits earned, current GPA, a declared major, sex, part-time or full-time enrollment status, ACT score, transfer status, and age. On average, the profile of an online student includes the following:

- Female with 66% of online course enrollments (see figure 14)
- Part-time. 46.73% of online students were part-time, compared with only 26.08% of face-to-face students (see figure 15)
- Higher ACT composite scores. Online students had an average ACT score of 20.77, 0.43 points higher than face-to-face students (see figure 16)
• More likely to be transfer students. 30% of online students were transfer students, while only 20% of face-to-face students had transferred to Russell (see figure 17).

• Older than face-to-face students. Online students had an average age at first enrollment of 19.33, while face-to-face students on average started at 18.80 years (see figure 18).

• Completed more credits than face-to-face students. Online students had completed an average of 84.71 credits, while face-to-face students had completed only 52.50 credits (see figure 19).

• Higher current GPAs. Online students had an average GPA of 2.76, 0.30 points higher on average than face-to-face students (see figure 20).

• More frequently declared a major than did online students. 93% of online students had declared a major, while only 87% of face-to-face students had done so (see figure 21).
Figure 14. A bar chart showing course enrollment by sex at Russell University.

Figure 15. A bar chart showing percent full-time students by course enrollment at Russell University.
Figure 16. A bar chart showing average ACT score by course enrollment at Russell University.

Figure 17. A bar chart showing transfer status by course modality at Russell University.
Figure 18. A bar chart showing mean age at first registration at Russell University by course modality.

Figure 19. A bar chart of average credits earned at Russell University by course modality.
In addition to the influence of these covariates, a significant effect of course enrollment in either online or face-to-face classes would have an impact on dependent
variables in the study: course grades, and student withdrawal rates. The baseline data show a significant imbalance between the treatment and control groups. See figure 22 for a visual representation of the imbalance between online and face-to-face groups. This chart shows the imbalance between face-to-face classes, with a negatively skewed distribution, and the online classes with a more normal distribution of scores.

Figure 22. A back-to-back histogram of treatment and control groups prior to matching based on data from Russell University.

Due to the imbalance between online and face-to-face groups with regards to multiple covariates, the researcher used a propensity score matching method to control for confounding covariates in determining significance of course outcomes. The following section will outline the validity and sensitivity of each of three different PSAs: near-neighbor matching, Mahalanobis’ distance matching metric, and optimal matching.
Following the analysis of each of these methods and their robustness with regards to the current data set, the researcher selected one method and conducted a two-sample \( t \)-test with the matched data to evaluate student grades and withdrawal rates.

**Propensity Score Matching: Validity and Sensitivity of Tests**

In order to minimize threats to the validity of the results, the researcher conducted three different propensity score matching methods. These methods included: (a) a greedy or near-neighbor matching method with both a 1:1 ratio and a 1:2 matching ratio, (b) a Mahalanobis distance matching technique, and (c) an optimal matching method with both 1:1 and 1:3 matching ratios. Each method yielded slightly different results in terms of balance of the matched data and with retention of cases. Analysis of the quality of the balance after propensity score matching and the relative number of cases included in the study was one statistical test that allowed for selection of the best PSA method for this specific data set.

Balance and retention of cases in the data are two ways to evaluate the quality of the match of the above propensity score methods. However, there is another important way to evaluate the fit of the three models tested in this study. Rosenbaum (2002) has developed a method to measure the sensitivity of a matching test to the possibility of hidden bias from variables not included in the model. A high sensitivity to hidden bias could mean that the model is not a good match for the study data, or could suggest that there are other variables not included in the study. The current study depends on data available through an institutional data set. Several factors listed by Tinto (1975, 1993) and Rovai (2003) such as computer literacy, information literacy, and family obligations
are not captured by institutional data, and are excluded from the study, which may introduce hidden bias. The Rosenbaum sensitivity analysis provides a statistical method that estimates the impact of these missing variables. For this study, the researcher conducted a sensitivity analysis for each of the tested matching models to facilitate the selection of the most robust model for inclusion in this study. The sensitivity analysis, together with balance and retention of cases determined the validity and sensitivity of each PSA method, and allowed the researcher to select the most robust PSA method to use in evaluating course outcomes for students in online and face-to-face classes.

**Near-neighbor Propensity Score Matching**

In a near-neighbor 1:1 matching method, each student in the online group (n = 1681) was matched with one student in the face-to-face group (n = 1681) to create a balanced model.

**Validity and Balance.** Of the 15 covariates in the sample, eight had a significant impact on the imbalance between enrollment groups prior to matching. These eight covariates include the maximum number of credits earned, current GPA, a declared major, sex, part-time or full-time enrollment status, ACT score, transfer status, and age. The seven covariates that did not have a significant impact on the balance of the model were race, first generation student status, high school GPA, veteran status, Pell Grant eligibility, income, and zip code. Balance for all covariates improved after matching. The poorest improvement was in the high school GPA variate, which improved by only 53%, but was not a significant contributor to imbalance in the model. The covariate of declared
major improved by 100% after matching. The balance of all covariates improved after matching.

A follow-up a Chi Square test after matching demonstrated that no significant imbalance remained after matching, $\chi^2 (15) = 13.2, p = .59$. See figure 23 for a back-to-back histogram showing the balance between online and face-to-face groups after 1:1 near-neighbor matching.

![Figure 23. A back-to-back histogram of online and face-to-face data after 1:1 near-neighbor matching.](image)

A near-neighbor matching model with a 1:2 ratio differed slightly from the 1:1 model. In this case, each online student ($n = 1,681$) was matched with the two nearest face-to-face students ($n = 3,362$), which maintains a larger sample size, but does not allow for as close a match as a 1:1 model. The 1:2 had the same covariates contributing to the imbalance of the model: the maximum number of credits earned, current GPA, a
declared major, sex, part-time or full-time enrollment status, ACT score, transfer status, and age. Race, first generation student status, high school GPA, veteran status, Pell Grant eligibility, income, and zip code did not have a significant impact on imbalance. However, the balance for all covariates did not improve in this model. For example, the quality of the Pell Grant eligibility match decreased by 25.31% through using this model, although all other covariates improved.

A follow-up a Chi Square test after matching demonstrated that, while improved over the original sample, a significant imbalance remained after matching, $\chi^2 (15) = 314, p < 0.001$. This lower balance is expected, given that a larger number of control students (3,362) were included in the 1:2 model than in the 1:1 model (1,681). This means that with two control individuals matched with each treatment individual, sometimes a poorer match was required. As additional data points are added back into the sample, the balance decreased. See figure 24 for a back-to-back histogram showing balance between online and face-to-face groups after near-neighbor 1:2 matching. This chart shows a poorer balance than 1:1 matching, but still shows improvement over baseline data.
In addition to evaluating balance and case retention for near-neighbor matching, sensitivity analysis provides an additional test for the robustness of this statistical model.

**Sensitivity Analysis for Near-neighbor Matching.** Using Rosenbaum’s sensitivity analysis on near neighbor 1:1 matching suggests that when $\Gamma \geq 1.20$, the association between student enrollment in an online class and student course grades would no longer be significant ($p = .12$). For the association between student course enrollment and withdrawal rates, when $\Gamma \geq 1.20$ the association would no longer be significant ($p = .07$). These results compare favorably with results for near-neighbor 1:2 matching, which also suggest that when $\Gamma \geq 1.20$, the association between student enrollment in an online class and student course grades would no longer be significant ($p$
For the association between student course enrollment and withdrawal rates, when $I \geq 1.20$ the association would no longer be significant ($p = .07$). After completing tests for validity and sensitivity for near-neighbor matching, the researcher conducted the same tests for the second PSA method: Mahalanobis metric matching method.

**Mahalanobis Matching**

The second model tested in this study was a Mahalanobis metric matching method. In this case, each online student ($n = 1,681$) was matched with the one nearest face-to-face student ($n = 1,681$) using Mahalanobis distance to determine the closest match for each online student.

**Balance of the Mahalanobis Method.** The Mahalanobis model had the same covariates contributing to the imbalance of as did near neighbor matching: the maximum number of credits earned, current GPA, a declared major, sex, part-time or full-time enrollment status, ACT score, transfer status, and age. Race, first generation student status, high school GPA, veteran status, Pell Grant eligibility, income, and zip code did not have a significant impact on imbalance. The balance for all variables improved after matching. Improvement in balance was most notable in veteran status, with a 100% improvement in balance, a declared major (95.70%), and in current GPA with improvement at 91.78%.

A follow-up a Chi Square test after matching demonstrated that, while improved over the original sample, a significant imbalance remained after matching, $\chi^2 (15) = 98.3$, $p < 0.001$. While this balance is improved over the baseline levels of imbalance, even after matching, there remained a significant difference between online and face-to-face
students with regards to the covariates tested in the study. Because of the nature of this statistical method, there is no back-to-back histogram available for Mahalanobis metric matching. After balancing the data, the researcher also conducted a sensitivity analysis for the Mahalanobis method.

**Sensitivity Analysis for Mahalanobis.** For Mahalanobis propensity scores, when \( \Gamma \geq 1.05 \), the association between student enrollment in an online class and student course grades would no longer be significant \((p = .09)\). For the association between student course enrollment and withdrawal rates, when \( \Gamma \geq 1.05 \) the association would no longer be significant \((p = .05)\). These results indicate that the Mahalanobis model is less robust with regards to missing confounding variables than the near-neighbor matching.

**Optimal Matching**

The final models tested in this study were two optimal matching methods: 1:1 matching and 1:3 matching. In the case of 1:1 matching, each online student \((n = 1,681)\) was matched with the one nearest face-to-face student \((n = 1,681)\) using a model that estimates the best fit for the dataset as a whole.

As with near-neighbor matching, and Mahalanobis metric matching, the same covariates contributed to the imbalance of the baseline data: the maximum number of credits earned, current GPA, a declared major, sex, part-time or full-time enrollment status, ACT score, transfer status, and age. Race, first generation student status, high school GPA, veteran status, Pell Grant eligibility, income, and zip code did not have a significant impact on imbalance. In this model, balance of most variables improved, although several saw a decrease in balance. Those covariates that saw a decrease in
balance included: first generation status, Pell grant eligibility, and zip code, however, none of these variables was a significant contributor to the baseline imbalance. Significant contributors, including maximum number of credits earned, current GPA, a declared major, sex, and part-time or full-time enrollment status all improved by more than 80%. Age showed only a 66.83% improvement, while ACT score, and transfer status had minimal improvement.

A follow-up a Chi Square test after matching echoed the above results, and demonstrated that a significant imbalance remained after matching, $\chi^2 (15) = 232$, $p < 0.001$. While this balance is improved over the baseline levels of imbalance, even after matching, there remained a significant difference between online and face-to-face students with regards to the covariates tested in the study. See figure 25 for a back-to-back histogram showing balance between online and face-to-face groups after optimal matching. The graph shows that after matching, there is greater balance between face-to-face and online student groups.
In the case of 1:3 optimal matching, each online student \((n = 1,681)\) was matched with the three nearest face-to-face students \((n = 5,043)\) using a model that estimates the best fit for the dataset as a whole. This model retains a larger proportion of the data points in the sample, but does not allow for as close a match as does 1:1 matching.

As with near-neighbor matching, and Mahalanobis metric matching, the same covariates contributed to the imbalance of the baseline data: the maximum number of credits earned, current GPA, a declared major, sex, part-time or full-time enrollment status, ACT score, transfer status, and age. Race, first generation student status, high school GPA, veteran status, Pell Grant eligibility, income, and zip code did not have a significant impact on imbalance. The balance for all variables improved after matching,
but in this case, improvements were smaller than in other methods. For example, improvement in balance in first generation student status was only 0.51%. The best improvements were in zip code (59.82%), high school GPA (47.04%), and veteran status (45.03%). All other factors had lower improvement after matching. Of the factors that had the most improvement, none were significantly contributing to the baseline imbalance of the model, suggesting that the resulting balance after matching is poor with regards to those key variables.

A follow-up a Chi Square test after matching echoed the above results, and demonstrated that a significant imbalance remained after matching, $\chi^2 (15) = 987, p < 0.001$. While this balance is improved over the baseline levels of imbalance, as expected with a 1:3 matching technique, there remained a significant difference between online and face-to-face students with regards to the covariates tested in the study. See figure 26 for a visual representation of balance between online and face-to-face groups after optimal 1:3 matching. After matching, there remains a significant imbalance between face-to-face and online student groups.
Figure 26. A back-to-back histogram of balance after 1:3 optimal matching.

In addition to these statistical tests for validity, the researcher conducted tests to evaluate sensitivity of this model to hidden bias.

**Sensitivity Analysis for Optimal Matching.** Optimal matching with a 1:1 ratio suggest that when $\Gamma \geq 1.20$, the association between student enrollment in an online class and student course grades would no longer be significant ($p = .08$). For the association between student course enrollment and withdrawal rates, when $\Gamma \geq 1.15$ the association would no longer be significant ($p = .08$). Optimal matching with a 1:3 ratio had similar but more sensitive results: when $\Gamma \geq 1.05$, the association between student enrollment in an online class and student course grades would no longer be significant ($p = .09$). For the association between student course enrollment and withdrawal rates, when $\Gamma \geq 1.15$ the association would no longer be significant ($p = .10$).
After examining all three PSA methods for validity and sensitivity, the researcher selected the one method that was the most robust to conduct final analyses and evaluate student outcomes.

**Selected Method and Results**

In order to conduct a final two-sample $t$-test to evaluate the effect of course enrollment on student course grades and withdrawal rates, the researcher needed to select the one statistical PSA method that was the most robust in terms of sample balance, retention of cases, and sensitivity to hidden bias. Using a measure for validity and sensitivity, the researcher selected the near-neighbor 1:2 ratio matching method as the most robust statistical model of those tested here according to the following rationale. First, this model is one of the two most robust models tested with regards to sensitivity, as both near-neighbor 1:1 and 1:2 matching were robust at the $I \geq 1.20$ level for both student course grades, and withdrawal rates from classes. Second, while the 1:2 ratio does not result in a sample as balanced as the 1:1 method, it does retain more students in the sample, and still has a significant improvement in balance over initial results. For these reasons, the researcher selected near-neighbor 1:2 matching as the most robust statistical model, and based final statistical tests on these matching results using a two-sample $t$-test.

**R1: Student Course Grades**

The first research question for this study asked: R1: To what extent does enrollment in a fully online class as compared to face-to-face classes affect course grades for undergraduate students who complete the course?
Results from a two-sample $t$-test on student course grades measured through average GPA, after using a near-neighbor 1:2 matching technique indicate that there is no statistically significant difference between online and face-to-face students, $t(3067) = 1.17, p = 0.24$). See figure 27 for average GPA for online and face-to-face students after matching. This plot shows non-significantly different average GPAs for face-to-face and online students.

![Boxplot of student average GPA based on course enrollment after near-neighbor 1:2 matching.](image)

Figure 27. Boxplot of student average GPA based on course enrollment after near-neighbor 1:2 matching.

These results of the 1:2 near-neighbor matching test contrast with baseline results, which indicated a statistically significant difference between groups, with a higher GPA for online students ($m = 2.55$) than for face-to-face students ($m = 2.34$), $t(7763) = -5.80$, $p<.001$). Prior to matching, online students showed higher GPAs at a statistically significant level, while post-matching results show a non-significant difference in
average course grades. These results indicate that there is no statistically significant effect of fully online course enrollment as compared to face-to-face course enrollment on student course grades for undergraduate students who completed the course. However, these results remain inconclusive, due to the sensitivity of this model to hidden bias. For this method when \( \Gamma \geq 1.20 \) the association would no longer be significant \((p = .14)\). This level of sensitivity suggests that these results are only 1.2 times more likely to be based on the effect of treatment rather than by chance, which is not a robust outcome. The reason for this sensitivity is due to missing or hidden bias from variables that were not included in the study. Because these results remain highly sensitive to hidden bias, this is not a highly conclusive outcome for the study.

**R2: Student Withdrawal Rates**

The second research question for this study asked: To what extent does enrollment in a fully online course as compared to face-to-face classes affect course withdrawal rates for undergraduate students?

Results from a two-sample \( t \)-test on student withdrawal rates after using a near-neighbor 1:2 matching technique indicated that online students have significantly higher withdrawal rates \((m = 0.09)\) than do face-to-face students \((m = 0.07)\), \( t(5041) = -2.76, p < .01 \). See figure 28 for a boxplot showing withdrawal rates for online and face-to-face students after matching. Online students have significantly higher withdrawal rates than do face-to-face students.
Figure 28. Boxplot of student withdrawal rates based on course enrollment after near neighbor 1:2 matching.

These results contrast with baseline results prior to matching, which suggested that there was no statistically significant difference between the withdrawal rates of online and face-to-face students $t(7763) = -1.07$, $p = 0.28)$. These results indicate that after propensity score matching, there is a statistically significant effect of enrolling in a fully online class as compared to a face-to-face class, with a higher withdrawal rate for students in online classes. These results also remain inconclusive, due to the sensitivity of this model to hidden bias. For this method when $\Gamma \geq 1.20$ the association would no longer be significant ($p = .07)$. This means that the odds that this outcome is an effect of course enrollment as opposed to other factors is only 1.2. As with the results for student course grades, a score of $\Gamma \geq 1.20$ suggests that these outcomes are only 1.2 times more likely to occur as an effect of treatment as they are to occur randomly. This is not a very robust
result, and indicates a hidden bias to missing confounding covariates that does not allow these results to suggest a strong conclusion.

**Summary**

Baseline data analysis suggested that there was a statistically significant effect of course enrollment on student course grades, with higher grades for online students. The same initial statistical analysis indicated that there was a non-significant effect of course enrollment on student withdrawal rates. After conducting three different propensity score analyses to find the best model fit for the current data, the researcher selected the near-neighbor 1:2 matching technique as the best combination of balanced data, retention of data points, and sensitivity to hidden bias. Final results indicate a contrast from baseline results, with a non-significant effect of enrolling in an online course on student course grades. There is a statistically significant effect of course enrollment on student withdrawal rates, with higher withdrawal rates for online students than for face-to-face students.
Chapter 5- Discussion and Implications

Summary of Findings & Related Literature

Student self-enrollment into online or face-to-face sections of a course can introduce a selection bias, or a difference in student characteristics between the two groups that can contribute to different course outcomes. It is important for the researcher to use a statistical method to control for these characteristics because a randomized control trial is not practical as a research method in an educational setting where student make their own enrollment decisions. The current study uses a propensity score analysis statistical method to balance out the bias introduced by student self-selection into online or face-to-face courses. The results of this study address the difference in student grades earned in different class modalities, and student withdrawal rates in online as compared to face-to-face classes.

Course Grades

The first research question in this study relates to student course grades: To what extent does enrollment in a fully online class as compared to face-to-face classes affect course grades for undergraduate students who complete the course? Results from this study indicate that prior to balancing the sample, students enrolled in online classes have higher course grades than do face-to-face students. After balancing data through a near-
neighbor 1:2 propensity score matching technique, results show that there is no
statistically significant difference between course grades for students enrolled in online
classes and those enrolled in face-to-face classes. These contrasting results suggest
controlling for confounding covariates is important in understanding the differences in
student course grades in different class modalities. Tinto (1973, 1995) and Rovai (2003)
suggest that possible confounders include student characteristics such as race, and
gender; student skills including digital and information literacy; external factors related to
family and work obligations; and internal academic factors such as social fit and
institutional commitment. After using a PSA to balance the sample and control for 15
different covariates related to Tinto (1973, 1995) and Rovai’s (2003) work, the balanced
sample showed that there was no significant difference between online and face-to-face
students. The reason for this difference is that prior to balancing the sample, older, more
experienced, high-achieving students with a declared major were more likely to take
online classes. In the baseline data, these characteristics helped to boost course grades,
but after controlling for these covariates, a balanced sample suggested that there was no
significant difference between groups.

A result of no significant difference in student course grades in an educational
context is a significant finding in this context. What this result means is that after
controlling for a variety of student characteristics, students enrolled in online and face-to-
face classes have no significant difference in their outcomes. This speaks to the quality
of an online education in terms of curriculum, course design, and instructor and
institutional support for students. Russell (1999) outlines the importance of this result in
defining the no significant difference phenomenon. This work states that in spite of some skepticism with regards to distance or online education, there is abundant research that indicates that students have similar outcomes in online courses. A result of no significant difference at Russell University means that students can expect to achieve the same learning objectives in these courses, and that they will have an equivalently robust educational outcome in an online classroom as they would in a face-to-face classroom.

The literature review for the current study indicates that of 35 studies with specific student outcomes, 21 demonstrate no significant difference in course outcomes among online and face-to-face students. The current study confirms that for course grades, after balancing enrollment groups, there is no significant difference among online and face-to-face students. Each of the previous studies that demonstrates no significant difference comes from a study with a relatively small sample focused on a specific subject (Dellana, Collins & West, 2000; Gutierrez & Russo, 2005; Leasure, Davis, & Theivon, 2000; McDonnough, Roberts & Hummel, 2014; Reuter, 2009; Rivera & Rice 2002; Summers, Waigandt & Whittaker, 2005; Waschull, 2001; Werhner, 2010). The number of data points in these studies range from 26 (Tseng & Walsh, 2016) to 1,907 (Euzent, Martin, Moskal & Moskal 2011). The current study corroborates these data, but expands on the sample, using a dataset of 156,161 unique data points aggregated into 7,765 individual students from all disciplines across campus rather than a small sample size from a specific subject area. These results are all consistent with the no significant different phenomenon outlined by Russell (1999) which argues that online classes can have no significant difference in course outcomes than face-to-face classes. The current
research is unique, however, in the scope of the data, including a larger sample size, and a broad student base that incorporated student data from across disciplines at Russell University.

**Withdrawal Rates**

The second research question in this study is related to student withdrawal rates: To what extent does enrollment in a fully online course as compared to face-to-face classes affect course withdrawal rates for undergraduate students? Preliminary results suggest that before balancing the sample, there is no significant difference between students taking online classes and students enrolled in face-to-face classes. After balancing data through a near-neighbor 1:2 propensity score matching technique, results indicate that there is a significantly higher withdrawal rate among students enrolled in online classes as compared with student enrolled in face-to-face classes. Again, having a balanced sample that controls for variables that introduce selection bias is important to understanding the differences in student withdrawal rates in online versus face-to-face courses.

In contrast to results from student course grades, data related to student withdrawal rates in the current study suggests that online students have withdrawal rates that are higher at a statistically significant rate than do their face-to-face peers. Five of the 35 articles in the literature review also showed significantly higher outcomes for face-to-face classes (Arias, Swinton & Anderson, 2018; Bunn, Fischer & Treba, 2014; Johnson & Palmer, 2015; Kaupp, 2012; Verhoeven & Wakeling, 2011). Of these five articles, none specifically tested for student withdrawal rates. While the current results
from these five articles follow the trend of suggesting better student outcomes in face-to-face classes, they do not specifically address the outcome of student withdrawal rates. The current study fills this gap in the literature by demonstrating significantly better outcomes for face-to-face students as they specifically relate to withdrawal rates. However, the results from the current study do validate results from three studies other studies that specifically used a propensity score method: each of these studies found higher withdrawal rates among online students than in their face-to-face peers (Smith, 2017; Xu and Jaggars, 2011a; Xu and Jaggars, 2011b). This current study is the only one of these works to specifically examine withdrawal rates at an HSI.

As with the results related to student course grades, the baseline data showed that online students are older, have more academic experience, and better overall GPAs. These factors mitigate the impact of online course enrollment, making the baseline data appear to have equal withdrawal rates as in face-to-face classes. However, after balancing the two enrollment groups through a PSA, results show that online students are withdrawing more frequently than do face-to-face students. These higher withdrawal rates could be related to factors introduced by Tinto that were not included in this study, such as computer skills, time management, and sense of belonging at the institution (Tinto, 1973, 1995).

While previous research has shown mixed results concerning course outcomes among online and face-to-face students, (Bunn, Fischer & Treba, 2014; Gregory, 2016; Hurlbut, 2018; Johnson & Palmer, 2015; Kaupp, 2012; Tseng & Walsh 2016; Verhoeven & Wakeling, 2011), the current study corroborates some of the trends noticeable in the
literature review. In the next section, this chapter will address the relationship between current results and studies related to Tinto (1975, 1993) and Rovai’s (2003) student integration theory before moving into a comparison with other statistically robust propensity score studies. Finally, this section will focus on how the current results relate to research conducted at Hispanic-serving institutions.

**Student Outcomes Using the Student Integration Model**

Tinto (1993) and Rovai (2003) indicate that many student factors that contribute to success in higher education. These factors include academic performance prior to enrollment in college, student skills, and factors both internal and external to the academic institution. The statistical results of the current study show strong support for the idea that a variety of variables contribute to the balance between students enrolled in online versus face-to-face classes. Of the 15 covariates in the sample, eight have a significant impact on the imbalance between enrollment groups prior to matching. This evidence suggests that maximum number of credits earned, current GPA, a declared major, gender, part-time or full-time enrollment status, ACT score, transfer status, and age all contribute to imbalance between online and face-to-face course enrollments.

Students in online classes are typically female, older, more experienced students, including more transfer students and those students with more completed credits than in face-to-face classes. Online students are also more likely to have a declared major, a higher GPA, and higher ACT scores, although they are also more likely to be part-time students. These results corroborate Tinto (1975, 1993) and Rovai’s (2003) model, which
acknowledges the contributions of a variety of academic and other factors on student success.

Previous literature related to online course outcomes, including student course grades, had very limited control for confounding variables (Dellana, Collins & West, 2000; Gutierrez & Russo, 2005; Leasure, Davis, & Theivon, 2000; McDonnough, Roberts & Hummel, 2014; Reuter, 2009; Rivera & Rice 2002; Summers, Waigandt & Whittaker, 2005; Waschull, 2001; Werhner, 2010). Of these studies, several did not control for any covariates (Gutierrez & Russo, 2005; McDonnough, Roberts & Hummel, 2014; Rivera & Rice 2002; Summers, Waigandt & Whittaker, 2005). Leasure, Davis, & Theivon (2000) controlled for the most covariates of these previous studies, and they included only five: age, GPA, earned credits, gender, and race.

Baseline results from the current study indicate that students enrolled in online classes earned higher course grades than did face-to-face students before controlling for 15 covariates. After controlling for these variables, the results turned out to be non-significantly different. These results indicate the importance of evaluating multiple student characteristics as introduced by Tinto (1975, 1993) and Rovai (2003), as baseline results for both course grades, and student withdrawal rates were significantly different from the results found after controlling for multiple confounding covariates.

**Student Outcomes in Rigorous Propensity Score Studies**

Among previous studies that have conducted rigorous propensity score studies controlling for multiple student characteristics, results are more conclusive: students in online classes earned lower course grades (Smith, 2017; Xu and Jaggars, 2011a, 2011b,
2013) than their face-to-face peers. These results differ from the results in the current study, which suggest that after controlling for student characteristics, there is no statistically significant difference in student course grades for those enrolled in online classes as compared to those enrolled in face-to-face classes. The results of the current study may suggest that curriculum and instruction in online classes provide an equivalent academic experience for students at this HSI.

Results from previous literature using a propensity score method to control for student outcomes indicate that students in online classes withdrew at higher rates than on-campus students (Smith, 2017; Wladis, Conway, and Hachey, 2015; Xu and Jaggars, 2011a, 2011b, 2013, 2014). The results of this current study are consistent with this previous research, as they indicate that online students at Russell University withdrew at higher rates than did face-to-face students.

**Student Outcomes in Online Classes at an HSI**

In the statistical analysis for this study, race was not a statistically significant contributing factor for imbalance between classes, indicating that although more than 25% of students enrolled at the institution are Hispanic, qualifying the institution for the HSI designation, these students do not have significantly different enrollment patterns than do students of other races. The impact of race on student outcomes is consistent with the one previous study of student outcomes at an HSI community college, which also found that student race was not a significant contributing factor in determining student grades in online classes (Wladis, Conway, & Hachey, 2015). This suggests that at an HSI, where 25% or more of the student population is Hispanic, race is not a
statistically significant determiner in whether students are more successful in online versus face-to-face classes.

The same previous research study found a significant difference in online and face-to-face course outcomes at an HSI community college, with higher successful course completion rates (grades C- or higher) for online students than for face-to-face students (Wladis, Conway, & Hachey, 2015). Results from this study do not agree with the results from Russell University. In the current study, there is no statistically significant difference among student grades in online and face-to-face courses. These results contrast with Wladis, Conway and Hachey’s (2015) findings that suggest better outcomes for online students. However, results from both the current study and the Wladis, Conway, and Hachey (2015) study both contrast with other propensity score research indicating statistically poorer course grades for online students (Smith, 2017; Xu and Jaggars, 2011a, 2011b, 2013). More research is needed to confirm this difference, but both the current study and the Wladis, Conway, and Hachey (2015) results demonstrate that there is a different performance pattern at Hispanic-serving institutions than at institutions that serve a more traditional population.

Implications

The implications of the study results could have an impact for many stakeholders at Russell University and other similar institutions. Online course enrollment has been increasing at United States institutions of higher education in the last decades (NCES, 2018). Additionally, among undergraduate students at four-year, public institutions, 31.7% of students enrolled in at least one distance education course in fall 2017 (NCES,
Nation-wide online course enrollment has increased steadily from 9.6% of in 2002 to 31.6% in 2016 (Allen & Seaman, 2014; Seaman, Allen & Seaman, 2018). This increase in online course enrollment has happened in spite of the trend of enrollment decline in the United States since 2012 (Seaman, Allen & Seaman, 2018). According to the Associate Vice President of Online Learning, Russell University has seen similar trends in their online course enrollment since online classes were first offered (AVP, personal communication, July 18, 2019).

After seeing many years of increasing online enrollments, institutions of higher education around the United States suddenly were forced entirely online in March 2020 in the wake of the COVID-19 pandemic, providing all students and faculty with an unexpected e-learning environment and decreased governmental restrictions on distance learning (Green, 2020). Given both these long-term and emergent trends, students, faculty members, and university administrators can all benefit from understanding the student outcomes in online classes. This understanding is particularly important at Hispanic-Serving institutions, where there has been limited research on the implications of online learning and the impact on student course outcomes.

Students are the primary beneficiaries of an online education, and it is important for students at HSI’s to receive an equivalent educational experience in their courses regardless of class modality. Given that the results of the current study show that students in online and face-to-face classes have non-statistically different course grades, this suggests an equitable experience for students who remain enrolled in courses and earn a course grade during the semester. This equivalent experience is important at all
institutions of higher education (IHE), but is particularly important at an HSI, where large populations of Hispanic students are enrolled. If race were a contributing factor to the difference in student course outcomes in different course modalities, as some research suggests (Kaupp, 2012; Koch, 2005), then this would introduce an inequity in the educational experience of students of color. However, at Russell University race was not a significant contributor to imbalance between online and face-to-face course enrollments. Students in online classes at Russell University are typically female, older, more experienced students, including more transfer students and those students with more completed credits than in face-to-face classes. Online students are also more likely to have a declared major, a higher GPA, and higher ACT scores, although they are also more likely to be part-time students at this particular HSI. Results from this study suggest that after balancing for these student characteristics, students in online and face-to-face classes have equivalent course grades. There is a lack of research specifically related to these outcomes at and HSI, and the results from Russell University provide initial results about the implications of online instruction on student performance and retention.

While students course grades are not significantly different between online and face-to-face classes, the results from this study indicate that students in online classes have higher withdrawal rates at a statistically significant level. This means that while students at Russell who remain enrolled in a course are equally likely to have the same outcomes, more students are withdrawing from online courses. Online students have an 8.8% withdrawal rate from classes, while face-to-face students have only a 7.2%
withdrawal rate. This difference of 1.6% is statistically significant, and demonstrates a strong relationship between online course enrollment and withdrawing from the class.

Retention of students at HSIs is a frequent topic of study, and other researchers have suggested methods for improving graduation rates and student performance at Hispanic-serving institutions (DiSanto and Guevara, 2019; Espinosa and Espinosa, 2012; Garcia and Ramirez, 2018; Martin and Meyer, 2010; Meling, 2012; Wolf, Lyons and Guevara, 2019). It remains important to engage students early, and to work with faculty to improve retention for online students. Other research in student retention at HSIs suggests ways to engage with students and help to improve student retention. Student engagement strategies and connections with faculty could both be implemented in an online environment. First, Meling (2012) suggests that the use of supplemental instruction can support Hispanic students and have a significant impact on their course performance. This supplemental instruction provides both additional academic resources to help students and a sense of community in a smaller learning environment. In addition to academic support, supplemental instruction provides for personalization of the course experience and a sense of connection between students and supplemental instructors, which is particularly important for Hispanic students.

Developing and maintaining this cultural community among Hispanic students can help them with their academic achievements (Martin and Meyer, 2010). This research suggests that building collaborative relationships, particularly between Hispanic students and faculty can improve student retention and graduation rates at HSIs. These collaborative relationships build on the sense of community that is important in Latinx
culture. Both personalized supplemental instruction and a focus on building relationships and community between students and faculty can happen in an online space. These interventions are important in improving the student academic experience at colleges, as student performance improves and allows students to complete classes and move towards graduation at a Hispanic-serving institution.

While implications for students are central to understanding the results of this study, there are also important considerations for faculty at the HSI. If those faculty members are aware that they can develop an online curriculum that provides for equivalent course grades for students, they may be more motivated to develop high quality online courses that attract and retain students. Course design of both online and face-to-face courses requires that faculty have administrative support, technological skills, and motivation to teach effectively online (Wolf, 2006). Well-developed courses can be a collaborative effort between faculty and instructional designers, with administrative support. Modelling this collaborative relationship between faculty and administration helps to advance the institutional culture of collaboration and collectivism necessary for students to thrive at an HSI (Martin and Meyer, 2010). The need for these intentional online instructional spaces is particularly important in an HSI environment (DiSanto and Guevara, 2019). Russell University has begun to provide instructors with training and support as they develop new online courses and revise previous classes, but additional administrative support and training through collaborative relationships is needed to further support instructional design in an equitable way that meets the needs of a Latinx student population (DiSanto and Guevara, 2019).
Equitable access to high-quality academic experiences helps to meet the needs of Russell’s diverse student population of non-traditional students, working students, and students with one or more dependents. Many of these characteristics are also associated with race at this HSI. While course grades are important, faculty should be aware that withdrawal rates are higher for online students at a significant level. Understanding this difference in the numbers of students who withdraw from online classes may motivate faculty to engage more with students, particularly in the first weeks of class before the withdrawal deadline. This faculty engagement and connection with students is particularly important with students who are part of Hispanic culture, which values community building and a sense of belonging. Other research in this field supports the need to build community among students and faculty in order to retain students at HSI’s. For example, Martin and Meyer (2010) explain the importance of building collaborative relationships between Latinx students and their instructors. These relationships help to improve student retention and graduation rates at HSI’s. Faculty at these institutions can also engage with students through undergraduate research opportunities (Garcia and Ramirez, 2018). Collective projects between faculty and Hispanic students in particular can help to build a communal learning space for students.

Faculty need to develop high quality courses and intentionally engage with all students in an online space, but at an HSI, it is particularly important to be aware of the value of engaging with Hispanic students and developing community in online courses. Providing online students with opportunities to develop community and participate in research projects with faculty members can greatly improve retention, particularly among
Hispanic students. While faculty play a key role in developing those relationships, to facilitate this faculty engagement, administrators at Russell should be involved in providing training and resources for faculty.

As an institution increases their number of course offerings, it can be important for the administration to understand the implications of greater online course enrollment. Results from this study suggest that students in online classes are having equivalent course grades to face-to-face students. These results may mean that the course development and instructional design at an institutional level is providing equivalent educational access for students, which is laudable. Those factors can provide evidence for administrators as they continue to dedicate time and university resources towards online course development. Conversely, higher withdrawal rates in online classes suggest room for improvement in how the institution supports online students. One factor that appears in other research is ensuring that online students have equal access to student support services. These services benefit Hispanic students at an HSI in particular by sharing social capital with students and helping them to succeed in their academic goals (Garcia and Ramirez, 2018). These resources could include access to mental health services, academic advising, degree transparency, and academic knowledge (Espinosa and Espinosa, 2012). Collectivism and social capital are valued in Hispanic culture, and providing high quality online support services can help these students to feel connected and to succeed academically. In order to retain a higher number of online students, the institution should provide high quality, robust academic experiences for both online and face-to-face students. They should also provide additional student support in the form of
online student services such as advising and mental health counseling to improve student retention for those taking online classes at an HSI.

Given the need for additional services to online students, student advising is one way that could help students to connect to the course modality that best fits their characteristics. At Russell, online students are also more likely to have a declared major, a higher GPA, and higher ACT scores, although they are also more likely to be part-time students at this particular HSI. If advisors understand these characteristics, together with student self-efficacy skills and time management abilities, they could advise students to enroll in either online or face-to-face sections of a course according to their skill set (Anderson, 2008). High quality advising for first-time college students could help reduce the significantly higher withdrawal rates seen in online classes at Russell. Museus and Ravello (2010) explored what high quality advising looks like for ethnic minority students, including Hispanic students. They found that advisors who humanized the academic process, used a multifaceted or individualized approach to advising, and who were proactive in connecting with students for advising were the most effective. These efforts to personalize the advising experience and foster a connection with the students help to improve student success and increase retention rates for Hispanic students. At an HSI, advisors should be particularly aware of the need to connect on a personal level with students to provide them with the academic support they need to succeed. First-generation, Hispanic students may not have the social and cultural capital they need to progress through their degree, and a personal, human connection with an advisor can have a significant positive impact on their success (Museus & Ravello, 2010).
While course grades for online and face-to-face students are not significantly different, online students at Russell have significantly higher withdrawal rates after controlling for student characteristics. At this Hispanic-serving institution, it is important to provide equitable access to education for students in online classes. This can be done by embracing students’ cultural priorities such as collectivism, sense of belonging and individualized support. Institutions can do this by supporting students through supplemental instruction and community building which help foster connections between students and faculty. Faculty can also contribute to student success by designing robust and inclusive course, and providing opportunities to connect and build community even in online spaces. Intentionally building a space where students can connect with each other and their instructors is particularly supportive for Hispanic students. Administrators should continue to support these efforts by providing access to student services by increasing access to advising and mental health services. Advisors should receive training on how to humanize and individualize the advising process in order to connect with students on a personal level as they reach out intentionally to Latinx students. By taking decisive action to support online students at this HSI, the institution can improve retention and reduce withdrawal rates across course modality.

**Limitations**

Propensity score analysis has a high degree of sensitivity to missing data (Guo & Fraser, 2015). As such, the researcher used a list wise deletion method to eliminate any cases that were missing data for any of the covariates. Covariates in this study with missing data included first generation status, ACT composite scores, High School GPA,
and income. Of these variables, only ACT composite scores were a significant contributor to imbalance in the model. However, this list wise deletion reduced the number of cases in the study, which can affect statistical power, and can introduce additional bias since the cases were not missing completely at random (MCAR).

**Recommendations for Future Research**

This study has introduced information related to online learning that builds on Tinto (1993) and Rovai’s (2003) research about student integration, but not all variables in their models were included in this study because of the limitations of a large data set. Russell University has started collecting data related to student sense of belonging, which fills in the gaps of internal factors that institutional data does not typically reflect. Conducting a similar study to the present research in five years when this information is more readily available for the whole student population would include variables that may be influencing the results of this study.

Additionally, one of the limitations of a study with a large sample size is the inability to describe the educational environment of each class. A similar study to the present research could be conducted that flags individual class types to evaluate how students perform with different subjects, experiential learning, labs, etc. in an online environment. Limiting the study to a smaller group of courses allows for greater exploration of the role of different pedagogical practices and the influence of the instructor in student outcomes in online courses. Adding specific course characteristics to the covariates examined in this study would provide a better example of the impact of educational context on student academic outcomes.
Furthermore, there has been a lack of research done at HSIs related to online course outcomes. More research is needed to confirm this difference, but both the current study and the Wladis, Conway, and Hachey (2015) results demonstrate that there is a different performance pattern at Hispanic-serving institutions than at institutions that serve a more traditional population. This performance pattern has only been suggested by the current study and one other study, demonstrating the need for additional research to validate this data pattern.

The results of the propensity score analyses used in this study show that data are highly sensitive to confounding covariates that might introduce hidden bias to the study. One way to balance this bias would be to conduct a smaller study that included a survey with additional data related to student skills, internal and external factors (Tinto 1993, Rovai, 2003). Student skills that could be collected in a survey include computer literacy, time management, and information literacy. Internal factors missing from the institutional data set include (a) social integration; (b) feeling a sense of belonging at the institution; (c) program fit, which is how well a student integrates with their major or academic program; (d) pedagogical preferences such as learning style, and (e) student feeling of satisfaction at the institution (Rovai, 2003). A survey could provide more complete information related to family circumstances and income, which are only included with a high degree of missingness in the current study. This survey could include qualitative elements that address student motivations for choosing to withdraw from classes. Future research with a survey would have a smaller data set, but a more
robust inclusion of covariates that could be influencing student course outcomes in a mixed-methods study.

Given the sensitivity of the current results to hidden bias (also known as selection bias), additional statistical tests could be included to account for some of that selection bias in the study that may not be accounted for by variables included in the study. Propensity scores methods in general do not control for hidden bias. One way to mitigate the effect of hidden bias would be to use a Heckman sample selection model. This two-step test would test for selection bias, and then offers a model to correct for that bias (Guo & Fraser, 2015).

Finally, given the current climate and institutional challenges associated with the COVID-19 pandemic, there are several opportunities for future research at Russell University. In an email to all faculty on May 13, 2020, the institution indicated that most classes that were originally scheduled in a face-to-face format will now be offered online in a new, online synchronous offering. Final numbers of class sections moving to this format will not be released until summer 2020, but the estimate is that at least two thirds of the 4,000 face-to-face classes will be offered in an online synchronous format. This new format allows room for a follow-up study to the current research dividing students into face-to-face, online synchronous (courses expected to be taught face-to-face, but moved online), and online asynchronous (traditional online) courses. This research could allow insights into the performance of students in a novel online synchronous format. It would also allow the institution to understand the online performance of students whose classes moved online, when the students were anticipating a face-to-face experience.
This same unprecedented move towards offering the majority of classes online will allow additional follow-up research to examine which student characteristics have a relationship with student course outcomes. This current research offers insights into student enrollment patterns based on their characteristics, which is slightly different than examining the correlation between characteristics such as race, gender, GPA and other variables as included in the current study, and student grades or withdrawal rates.

The research in the current study is highly relevant in an academic climate where online course enrollments are increasing, and the COVID-19 pandemic has made this research even more urgent as institutions of higher education strive to meet student needs in a changing environment. Along with the unprecedented times, there are also unprecedented opportunities to conduct research that will benefit students, faculty, and institutions as we recover in a post-pandemic world.
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