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Influence of Reading Proficiency on Placement and Success in Online Developmental Mathematics

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This is to certify that the doctoral dissertation by

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Walden University
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MA, Northern Arizona University, 1999

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Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

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Abstract

Community college leaders have spent years trying to improve success rates for students in developmental mathematics (DM) courses, but with little progress. This quantitative study, using a pre-experimental static-group research design, examined if a change in a community college district's policy and practices for student placement into DM courses could improve student success in online DM courses. Bounded rationality theory provided the lens to view how students' decision making is influenced by the lack of timely and appropriate information during the placement process. The study addressed whether a composite placement score, the result of combining the ACCUPLACER placement scores for elementary algebra and reading comprehension, would improve predicting student success in the online DM courses of basic arithmetic and introductory algebra. Logistic regression was used to analyze archival data from a student population of 39,585 students from which 767 participants were identified using a stratified random sampling method. The findings indicated that the composite score was a statistically significant predictor of the likelihood of student success only for the online basic arithmetic course ($\beta = .024$, Exp(β) = 1.024, $p < .0005$), which means the higher the composite placement score, the greater the likelihood of success. Providing DM students with information on reading proficiency's influence can increase student success rates. The social change implications are that when students are placed properly in a DM course they complete the sequence in less time, reach their academic goals sooner, and spend less money. In turn, the community college and local community also benefit.

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Dedication

My dissertation is dedicated to my loving husband, whose unwavering support and endless patience made this a successful journey. His continued encouragement and faith in my ability provided the often-needed motivation to keep going. I also dedicate this dissertation to my family, specifically my youngest child whose daily support was vital to the completion of the entire process. Thank you all so much for your support during these four years.

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Chapter 1: Introduction to the Study

Educational researchers and community college leaders have spent more than 20 years trying different approaches for meeting the needs of academically underprepared students including addressing their identification process, their academic needs, and their success in developmental mathematics (DM) courses, but with limited progress (Center for Community College Student Engagement, [CCCSE], 2016; Ireland, 2015). Community college leaders have the responsibility to ensure that their students are prepared for a life of independence, employment, and lifelong learning (Ben-Jacob, 2016). The CCCSE (2016) indicated that success in postsecondary training increases a person's ability to earn a livable wage, support a family, contribute to the local economy, and participate in the democratic process. Bohlig et al. (2018) observed that some postsecondary institutions have been challenged to double student success rates in developmental education (DE) courses and in these students' first college level course. While earning a college certificate or degree is often considered central to success for individuals and society, leaders at community colleges continue to grapple with how to meet the academic needs of their academically underprepared students (Bahr, 2010).

One of the challenges faced by community college leaders is the increased need for online and face-to-face DM courses attributable to the upsurge in the number of academically underprepared students (Cho & Heron, 2015). Sixty-eight percent of the students classified as academically underprepared require at least one developmental course, of which mathematics is the most common (Chen, 2016). Similarly, Okimoto and Heck (2015) reported that over 70% of the students classified as underprepared for college courses required DM. Adding to this challenge, Jaggars, Hodara, Cho, and Xu (2015) observed that that the high number of underprepared students could originate from an error in community colleges' student placement policies and practices. The placement of students into a DM course sequence requires an efficient and effective policy for collecting data and accurately determining which students are college ready and which need DM (Belfield, 2014; Scott-Clayton & Stacey, 2015). In addition to placement concerns, there are concerns about student success in DM courses.

Student success at the community college level continues to be the focus of educational researchers (Bohlig et al., 2018; Ireland, 2015). Fong, Melguizo, and Prather (2015) studied community college students' success rates for course and sequence success rates in a four-course sequence of DM, where success in a course was defined as earning a grade (A, B, or C) and allowed the student to enroll in the next course in the DM sequence or a college level course. This definition of success was used in this research.

Fong et al. (2015) documented that only 11% of the students who entered a developmental sequence at the lowest level (arithmetic) successfully completed the sequence and continued to their first college level mathematics course. However, 73% of students that began at the highest level of the sequence (intermediate algebra) continued on to their first college level mathematics course (Fong et al., 2015). Fong et al. (2015) also observed a sequence success rate of 38% for those students who started two levels (elementary algebra) below college-level level, while students who started in prealgebra (three levels below college level) had a sequence success rate of 17%. These results indicated that where a student enters the DM sequence influences whether that student is successful. The success rate data presented by Fong et al. (2015) enabled a comparison of UCCCD for this study.

Nationwide, 62% of students in online DM courses and 43% of students in face-to-face DM courses failed their courses (e.g., did not move on to the next level) because of (a) the lack of course completion or (b) a final grade of D or F (Jaggars, Edgecombe, & Stacey, 2013). Moreover, many students repeat DM courses because of a failing grade (D or F) or withdrawing (W) and eventually quit college without attaining the skills or credentials needed to meet their academic or career goals (Cox, 2015; Gomez et al., 2015). Based on previously noted research results, low student success rates have been linked not only to initial placement of students in a DM course sequence, but also to modality.

As a result of this low rate of student success (as measured by a final grade of D, F, or W) in DE courses, many community college leaders have adjusted the placement policies and practices, course content, and modality (online, hybrid, and face-to-face) in hopes of improving student success rates in developmental courses, but with minimal improvement (Bohlig, et al., 2018; Hodara & Lewis, 2017; Shukla, Hassani, & Casleton, 2014). Students in a DM course sequence often add as many as five additional semesters prior to enrolling in their first college-level mathematics course (Crisp & Delgado, 2014). Hence, this additional time spent in college contributes to additional costs to students and to the community college for remedial course that may or may not be effective.

Spending time in DE courses and/or repeating these courses increases students' expenditures (e.g., money and time) associated with attending college to improve their future earnings (Silver-Pacuilla, Perin, & Miller, 2014). According to a 2015 study, community college leaders spend 4 billion dollars each year on DE programs that may or may not be effective (Rodriguez, Bowden, Belfield, & Scott-Clayton, 2015). Parker, Traver, and Cornick (2018) concluded that the challenge faced by community college leaders is to ensure that all students, but specifically the mathematically underprepared students, have the opportunity to develop the mathematical literacy necessary for them to attain the degree or credentials required for participation in the global economy. Therefore, making informed decisions during the placement process would reduce the cost of a community college education for both the student and the institution.

Today, the challenges still exist for researchers and community college leaders to identify, understand, and meet the academic needs of students who require developmental courses, specifically DM (Pruett, & Absher, 2015). Wolfle and Williams (2014) concluded that demographic data failed to explain low success rates in DM courses and encouraged researchers to focus on other factors that contribute to success and persistence. In fact, Wolfle and Williams concluded that only 3.8% of the variations in success and persistence rates in DM courses are explained by "developmental status, age, race, ethnicity, and gender" (p. 148). Based on the recommendation of the previously noted authors that demographic characteristics account for a small percentage of the variations in student success rates, I did not include these characteristics in my analysis on student success rates in online DM courses.

My study examined reading comprehension as a potential predictive factor based on previously noted research findings that indicated a lack of understanding about which factors could improve predicting students' success. Reading comprehension as a predictive factor has not been the focus of research on student success in DM nor in student placement policies and practices at the community college level. Students use their reading comprehension skills to gather information about a specific mathematical task, but when students struggle in mathematics they tend to also struggle with reading comprehension (Nortvedt, Gustafsson, & Lehre, 2016). For this study, I used historical student data from an urban county community college district (UCCCD) located in the southwestern part of the United States. I examined the influence that a composite placement score, based on the summation of the ACCUPLACER mathematics and reading comprehension placement scores, had on student placement and subsequent success in online and face-to-face DM courses. In this chapter, I included a discussion on the research purpose, background information, nature of the research, and theoretical foundation. Additionally, I discussed the research problem, research design, and research questions.

Background

Community colleges educate over half of American undergraduates (Bailey & Jaggars, 2016). Nationwide, between 60% and 70% of freshmen community college students require academic support in at least one DE course (reading, writing, and/or mathematics) prior to taking college-level courses (Melguizo, Bos, Ngo, Mills, & Prather, 2016; Rodriguez et al., 2015). Bailey and Belfield (2015) concluded that most community college DE programs fail to meet the expectation of preparing students for college-level courses because a majority of students did not complete the DE sequence required for enrollment in college-level courses. Despite community college leaders implementing a variety of methods and services to improve success rates in DE courses, student rates of success continue to be dismal (Hawley & Chiang, 2017).

In a national study of 3,476 first-time college students, Fike and Fike (2012) revealed that students who failed their DM course were 81.2% less likely to continue towards a degree than students who were college ready. In comparison, UCCCD reported that of the first-time students enrolled in one or more DE courses in the Fall 2014 term, 41% failed to successfully complete the lowest level DM course (basic arithmetic), 36% failed to successfully complete the highest-level DM course (introductory algebra), and 23% failed to successfully complete the highest-level developmental reading course (college reading skills). These UCCCD findings represented all DM courses and the DE reading course regardless of modality. The lack of student success (i.e., progression through each course of the sequence) in DE courses (e.g., mathematics and reading), whether if at a 2-year or 4-year institution, prevented these students from attaining their academic goal (Boatman & Long, 2018; Fike & Fike, 2012; Wolfle & Williams, 2014). The most commonly studied topic among DM researchers is the lack of student success (Boatman & Long, 2018; Fong et al., 2015; Shukla et al., 2014) and misplacement of students into DM courses (Ngo, Chi, & Park, 2018; Scott-Clayton & Stacey, 2015). Hence, it is important to understand how a student’s reading proficiency could influence placement and their success in DM courses.

Currently, there is a dearth of studies addressing reading comprehension as an aspect of placement into DM courses or reading proficiency (comprehension) as a predictor of student success in community college DM (Fike & Fike, 2008; Roberman, 2014). Poole (2016) observed that the lack of strong reading comprehension skills and background content knowledge hindered college students' ability to read and comprehend college textbooks (e.g., mathematics), which contributed to the lack of student success. Similarly, Xu (2016) stated that an increase in reading proficiency had a positive influence on student achievement in community college DM courses. Boatman and Long (2018) argued that community college students in DE reading courses are likely to also be enrolled in a DM course. While there is limited research on linking reading proficiency and DM course success in community college, the mathematical content of DM courses is similar to the mathematical content found in Grades 3 to 11.

Adelson, Dickinson, and Cunningham (2015) conducted a longitudinal study in which they found a strong relationship between mathematical achievement and reading proficiency in Grades 3 to 11. Korpershoek, Kuyper, and van der Werf (2015) also documented a strong relationship between mathematics achievement and reading ability in high school advanced mathematics. As a result of the limited number of studies on reading comprehension and mathematics at the community college level, the findings of studies that focused on the reading proficiency and mathematical achievement in Grades 3 to 11 are relevant to this study. More details on the influence of reading comprehension on mathematics success can be found in Chapter 2.

The number of students entering college underprepared for college-level mathematics creates challenges for postsecondary institutions (Boatman, & Long, 2018). In a study of 57 community colleges, researchers pointed out that 59% of incoming students required DM courses (Bailey, Jeong, & Cho, 2010). Researchers noted a lack of standard placement processes among postsecondary institutions, which can lead to the misplacement of students into DM courses (Scott-Clayton & Stacey, 2015). As a result of their findings, researchers argued the need for additional studies on placement policies and practices (Acosta, North, & Avella, 2016; Scott-Clayton & Stacey, 2015).

Some authors also remarked on the need for further studies on the influence that instructional modality (online, hybrid, and face-to-face) has on underprepared students' success (Ashby, Sadera, & McNary, 2011; Jaggars et al., 2013; Jones & Long, 2013; Nguyen, 2015). Online learning is increasingly available as an instructional modality for developmental courses in mathematics to meet the demands of students (Acosta et al., 2016; Rodriguez et al., 2015). However, existing research indicated that few of the changes proposed and tested (e.g., placement and modality) significantly increased the rate of student success in DM courses (Hawley & Chiang, 2017; Xu & Jaggars, 2011a).

This research addressed a gap in knowledge and adds to the literature by examining the influence a placement score that includes reading proficiency has on determining student success in online community college DM courses. As previously discussed, this research was needed because of the high failure rate in online community college DM courses.

Problem Statement

For this study, I examined the problem of community college students' low success rates in online DM courses and relied on current findings from the field of DM that represented the seminal work of earlier authors. To address the increase in the number of students requiring DM courses, community college leaders have increased the number of online DM courses even though researchers have noted the low student success rates and high student withdrawal rates among online courses (Acosta et al., 2016; Jaggars et al., 2013; Xu & Jaggars, 2013). Thus, this problem is current, relevant and significant.

Many authors reported that student success rates in online courses, regardless of whether they were developmental or college level, were lower than traditional face-to-face courses (Ashby et al., 2011; Wolff, Wood-Kustanowitz, & Ashkenazi, 2014). These lower success rates for online DM courses were attributed to higher rates of student withdrawal when compared to face-to-face DM courses (Ashby et al., 2011; Wolff, Wood-Kustanowitz, & Ashkenazi, 2014). It has been observed that students drop out of online courses because students fail to understand that online courses are not necessarily easier than the traditional, face-to-face modality, and that online courses require substantial independent reading (Lee & Choi, 2011). Boatman and Long (2018) suggested that students who placed into a DM course, and had a low reading comprehension placement score, should consider taking a developmental reading class to improve their success. Wolfle and Williams (2014) concluded that one way to improve success rates in online DM courses was to dissuade academically underprepared students from enrolling in these courses. Kauffman (2015) argued that placement policy and practices need to address the fact that online courses are not appropriate for all students. The findings of Wolff et al. (2014) and other authors previously noted, corroborated that both mathematics proficiency and reading proficiency, along with course modality, were significant predictors of student success. The previously noted authors also referred to the role that placement policies and practices contributed to lower student success rates in DM courses.

The identification of students who are insufficiently prepared and the placement of these students into DM sequences vary among postsecondary institutions. Some postsecondary institutions use specific cut scores on standardized assessments, such as the ACT, PSAT, and SAT, to determine college readiness (National Center for Public Policy and Higher Education, 2010). Many community college students take a placement test (e.g., ACCUPLACER, COMPASS, or ALEKS) to determine if they have the academic skills needed to be successful in college-level courses (Ngo & Kwon, 2015; Rodriguez et al., 2015). My study examined the placement policies and practices used at UCCCD.

UCCCD, with 10 individually accredited colleges, has a yearly student population of over 150,000, a yearly average of 12,000 students enroll in DM courses, and 5,000 students enroll in developmental reading courses. UCCCD’s 10 colleges use ACCUPLACER mathematics test scores to place students into DM courses. Sixty-seven percent of first-time UCCCD students require DM, which is similar to the nationally reported average. The UCCCD student enrollment in DM courses increased by 24.4%

from Fall 2014 semester (10,134 students) to Fall 2015 semester (12,607 students). The DM course success rate also steadily increased from 50% in 2012 to 60% in 2016, again success rates are similar to the nationally reported rates.

In order to identify a meaningful gap in the current online DM research literature, I searched Google Scholar, Educational Resource Information Center (ERIC), ProQuest Dissertation and Theses, ProQuest Center, Dissertations and Theses @ Walden, PsycINFO, and Sage journals. The searches turned up few studies that focused on community colleges' placement policies and practices, nor on student success in online DM courses that used only reading proficiency and mathematics placement to identify students who required DM courses. Hence, this research addressed a meaningful knowledge gap in the current online DM research literature.

Purpose of the Study

The purpose of this quasi-experimental quantitative study was to examine whether a change in UCCCD's policy and practices for student placement into online DM courses could improve predicting the likelihood of student success. The variables were student success (dependent), modality (independent), and the composite placement score (independent) consisting of reading comprehension and math proficiency. Bohlig et al. (2018) concluded that, because of the complexity of community college students' lives, the identification of student characteristics as key variables was not feasible. As noted earlier, Wolfle and Williams (2014) reported that variations in success rates in DM courses are not explained by demographic characteristics. For this reason, my research focused on the influence that the addition of reading comprehension had on student placement and success given that a majority of first-time UCCCD students are required to take placement tests for mathematics and reading. Hence, this research did not include demographic data, student characteristics, institutional characteristics, previous college, or high school experiences as confounding predictive variables.

Research Questions and Hypotheses

The following questions guided this study:

Research Question 1: To what extent does a composite placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course basic arithmetic where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, introductory algebra?

$H_0$1: There is not a statistical and significant difference in predicting the likelihood of student success with the use of a composite placement score in the online DM course Basic arithmetic.

H_A1: There is a statistical and significant difference in predicting the likelihood of student success with the use of a composite placement score in the online DM course basic arithmetic.

Research Question 2: To what extent does a composite placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course introductory algebra, where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, intermediate algebra?

$H_0 2$: There is not a statistical and significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course introductory algebra.

$H_A 2$: There is a statistical and significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course introductory algebra.

Theoretical Framework of the Study

Simon's (1947) bounded rationality theory, a social change theory, provided the theoretical framework for this research. Simon's bounded rationality theory was the result of his interest in the literature on decision making (also known as heuristics) and the elements of cultural-cognition or cultural capital (Simon, 1976, 1979, 1982). My research does not set out to prove the theory. Instead, Simon's bounded rationality theory was used as a narrative to explain decisions made by community college leaders and students concerning student placement in the online DM course of basic arithmetic and introductory algebra.

Bounded rationality theory contends that organizations and people make decisions under the pressures of (a) time, (b) incomplete information, and (c) limited cognitive understanding of how a system works (Simon, 1947, 1957, 1976). Simon (1976), as the seminal author of bounded rationality theory, concluded that organizational stakeholders, performing as decision makers, typically do not make an optimal choice, instead select the option that is satisfactory and suffices, or satisficing. The bounded rationality theory provides a view of how students, as decision makers, approach their selection of developmental course modality. UCCCD, like so many other community colleges, continue to offer online DM courses, despite continuing low success rates. By using the findings of my study, UCCCD students, as decision makers, will be able to make an optimal decision on whether to take their DM course online or in a face-to-face classroom environment.

Nature of the Study

A pre-experimental, static-group comparison research design was used for this quasi-experimental quantitative study. The rationale for using this specific design was that this research design connected to the research questions by addressing whether a treatment variable (e.g. modality and/or composite placement score) caused an increase in the likelihood of student success (Campbell & Stanley, 1963). My study used logistic regression models to examine if predictor variables based on ACCUPLACER scores and modality were statistical and significant predictors of student success in the online DM courses basic arithmetic and introductory algebra. For this study, logistic regression was the best fit as the outcome variable was dichotomous with both continuous and binomial predictors (see Field, 2011). UCCCD's Office of Institutional Effectiveness provided the historical data used in my study. The student data was drawn from information that was routinely collected during the admissions process and from information on final course grades provided by instructors. The participants must have taken the placement tests for mathematics and reading comprehension during the period of August 1, 2014, to January 19, 2017, and attempted a UCCCD DM course (basic arithmetic or introductory algebra) between the Fall 2014 term and the Spring 2017 semesters, with no summer sessions included.

Definitions

Bounded rationality: Bounded rationality describes the processes used by students and institutions to make an academic decision, but which can be limited (bounded) for the problem solver by a lack of time, knowledge, and cognitive ability (Simon, 1957, 1979).

College-ready: "College readiness can be defined as the level of preparation a student needs to enroll and succeed—without remediation—in a credit bearing general education course at a post-secondary institution that offers a baccalaureate degree or transfer to a baccalaureate program" (Conley, 2007, p. 5).

Cultural capital: Cultural capital suggests that students' education decisions and practices are the results of cultural resources that are handed down, which include social background, parents' educational level, and readiness to learn (Cincinnato, Weaver, Keer, & Valcke, 2016).

Developmental education: Developmental education supports the academic and personal growth of underprepared college students through instruction, counseling, advising, and tutoring. The clients of developmental education programs are traditional and nontraditional students who have been assessed as needing to develop their skills in order to be successful in college (National Center for Developmental Education, NCDE, 2017).

Gate-keeper courses: Gate-keeper courses are defined as "the first college-level math or English courses—within two years" (Fong, Melguizo, & Prather, 2013. p. 1). UCCCD defines this as those courses in which a large number of students fail to complete successfully.

Nontraditional students: Nontraditional students are students who are described by any combination of the following seven characteristics: "delayed enrollment into postsecondary education; attends college part-time; works full time; is financially independent for financial aid purposes; has dependents other than a spouse; is a single parent; or does not have a high school diploma" (Pelletier, 2010, p.1).

Persistence: Persistence is defined as "continued enrollment (or degree completion) at any higher education institution—including one different from the institution of initial enrollment—in the fall semesters of a student's first and second year" (National Student Clearinghouse Research Center, 2016, "Figure 1 Note").

Program for International Student Assessment (PISA): An international assessment given every three years to 15-year-old students from 65 different countries or jurisdictions. The 2009 assessment focused on reading literacy with science and mathematics (Ercikan et al., 2015).

Progress in International Reading Literacy Study (PIRLS): An international assessment of literacy (reading comprehension) given to children in the fourth grade. (Mullins & Martin, 2015).

Retention: Retention is defined as "Continued enrolment (or degree completion) within the same higher education institution in the fall semesters of a student's first and second year" (National Student Clearinghouse Research Center, 2016, "Figure 1 Note").

Success: Success is defined as earning a grade (A, B, or C) that allows the student to enroll in the next course in the DM sequence or a college level course (Fong et al., 2015).

Trends in International Mathematics and Science Study (TIMSS): An international assessment of mathematics given to children in the fourth and tenth grade. (Mullins & Martin, 2015).

Assumptions

The intent of this study was to determine if a composite placement score (based on the summation of the reading comprehension placement score and the mathematics placement score) and course modality improved the ability to predict the likelihood of student success in online DM courses. The first assumption was that students put their best effort towards answering the questions on the ACCUPLACER reading comprehension and mathematics placement tests. A second assumption was that students put forth their best effort into all assessments of the DM course, and that the students' final grade in the course was an accurate reflection of the student's work and achievement. A third assumption was students who withdrew from the course could represent a mortality-confounded variable. To address this concern, students who withdrew after the seventh week were included in the sample population, while students who withdrew by the end of Week 7 were not included in the sample population. Those students who withdrew after the Week 7 were classified as not successful, which was the same as with students who earned a final grade of D or F. Lee and Choi (2011) identified nine factors that influenced students to withdraw from online courses and sorted them into three categories: “student factors, course/program factors, and environmental factors” (p. 593). The reasons why students withdrew was beyond the scope of this research. A fourth assumption was that students self-selected the modality of their DM course. The final assumptions are that during the years targeted for this study (a) that the adopted curriculum used was MathAS and (b) that each campus developed and mandated a common final exam. These assumptions made during the design of this study represented aspects of the research that are believed but cannot be demonstrated to be true, but are critical in the context of my study.

Scope and Delimitations

The setting for this study was an urban county community college district (UCCCD) located in the southwestern part of the United States. UCCCD has 10 individually accredited colleges with a yearly student population of over 150,000. For this study, one college was not included as this campus offers only online courses, which could bias the results as students do not have the option of selecting face-to-face modality. The data collected represented students enrolled in the nine remaining campuses.

The scope of this research problem was limited to the domain of DM courses and modalities of online and face-to-face classrooms. The boundaries of this research were defined by the populations that were included and those that were excluded. The work of Banerjee and Chaudhury (2010) provided guidance on identifying the population, targeted population, and sample populations. The population represented all community college students who enrolled in a DM course, while the target population were all students who had enrolled in a DM course between the Fall 2014 and Spring 2017 semesters at any of the nine UCCCD campuses. Sample populations were the result of a stratified random sampling, which resulted in samples that were proportionally representative of the targeted population's characteristics (see Table 3). Excluded participants were those students who attended a UCCCD campus that only offered DM courses online, who were under the age of 18, and who did not have an ACCUPLACER elementary algebra or reading comprehension placement score.

Next, the boundaries of the study were also defined by the theoretical framework that was most related to the area of DM that were not investigated. I did not use a theory that relied on student demographic characteristics (e.g. age, ethnicity, college history, family history, socioeconomic identifier, or gender). As previously noted, demographic characteristics of students in DM courses have extensively been explored using cultural capital theory (see Chapter 2 for more detail). Instead, I chose Simon's (1947) bounded rationality theory, which provided a lens for viewing the decision making process from an individual and institutional perspective. Bounded rationality theory also provided the lens from which to view placement policies and practices that influence student success in online DM courses.

The potential findings of this research could be generalized to all community colleges that use ACCUPLACER as a predictor of student success in DM courses. The results of this study are generalizable because the study had a large targeted population from which the sample populations were chosen and because the study represented three years of student data (i.e., a longitudinal study). Colleges using multiple measures for placement or do not assess reading comprehension proficiency may not find this study generalizable to their setting.

Limitations

The use of archival (i.e., historical or ex-post facto) data could be a limitation. Johnston (2014) noted that the lack of participation in the process of collecting data prevents a researcher from identifying or understanding problems that could occur. Archival data was the only data that I had access to for my study. I have been assured that data collection was a routine process within UCCCD, which signified that there was no need to address this limitation.

Another limitation could be the removal of students who had withdrawn from the DM courses before the seventh week. The decision to not include these students was based on similar studies. Fong et al. (2015) removed students from their study if they withdrew on or before the college's no-penalty drop date. The rationale for not including these students was also based on the work of Conchran, Campbell, Baker, and Leeds (2014) who noted that students withdraw for many different reasons (e.g., academic, personal reasons). The UCCCD Office of Institutional Research indicated that students are not penalized if they withdraw prior to the seventh week and are assigned a W (passing prior to withdrawing, not computed in the grade point average). Determining the exact reasons why students withdrew from a DM course during the time period of this study would require data from interviews or surveys, which was not within the scope of this study.

Another limitation was the lack of randomness in placement of students in each of the developmental courses (basic arithmetic or introductory algebra), as students are referred to a specific DM course based on their ACCUPLACER mathematics score. In addition, students were free to choose the modality (online or face-to-face) that best met their academic and personal needs, which represented another situation where the research lacked randomness. Also, I had no control over which course a student was referred, which course they actually enrolled in, or which modality the student chose. Addressing these limitations, my research included only students who meet the sampling criteria: had ACCCUPLACER placement scores for reading comprehension and elementary algebra, 18 years of age or older, stayed enrolled in a DM course after Week 7, and earned a letter grade of A, B, C, D, F, P, or W.

Significance

The failure to address the reasons why students have low success rates continues to create challenges for academically underprepared community college students who require DM courses. Students required to take DE courses must spend additional time and money before enrolling in college-level classes (Crisp & Delgado, 2014; Ngo & Melguizo, 2016). Researchers reported that students who require DE courses could spend up to five years to earn one year of transferable courses, which influences the long-term opportunities for these students (Fong et al., 2015).

Yearly, postsecondary institutions spend 5.6 billion dollars on developmental programs (Boatman & Long, 2018). Jimenez, Sargrad, Morales, and Thompson (2016) reported that nationally students spend 1.3 billion dollars on remediation. The cost of remediation is high for both students and the colleges. However, the continued failure of postsecondary institutions to provide students an appropriate and supportive placement process prevents them from fulfilling their academic and life's goals, as well as closing the lifetime earning's gap between high school and college graduates (Boatman & Long, 2018; Dynarski & Scott-Clayton, 2013). Community colleges, as educational organizations, need to remove policies and practices that create barriers for students (Bang & Vossoughi, 2016; Stephan, Patterson, Kelly, & Mair, 2016). As previously noted, community college leaders can begin the process of change by applying bounded rationality theory to decision making at the placement policy level and student level. Providing students with appropriate and timely knowledge about the placement process, policies, and practices could remove barriers to better decision making by students, which could lead to higher success rates and decreased time and money spent on DM.

The results of my study indicate to community college leaders, mathematics faculty, and students that a composite placement score could improve predicting the likelihood of student success in online DM courses. The findings could be used by advisement personnel to inform students about whether a certain modality would better fit their academic needs. The significance of my study was that it provides information on the issue of student success in online DM courses. The results of this study support changing the placement policy and practices for placing students into DM courses. Furthermore, the results provide information to both postsecondary institutions and students about which modality, based on placement scores, best meets students' academic skill level and needs thus improving success rates in online DM courses.

Summary

Community college students are failing online DM courses at a rate higher than those students in the same face-to-face classroom. This signifies that those students who fail a DM course do not acquire the needed mathematics skills required for the next mathematics course or the skills specific to their area of study. As a social change concern, this failure creates a barrier that thwarts students from completing the academic requirements for a chosen career field, as well as, meeting and attaining their life's goal of economic and social advancement. The purpose of this quasi-experimental quantitative study was to examine whether a change in UCCCD's policy and practices for student placement into online DM courses could improve predicting the likelihood of student success. Simon's (1947) bounded rationality theory provided the lens to view community college students' decision making process when selecting whether to enroll in an online or face-to-face DM course. This first chapter included a summary of the topic and background of online DM courses in community colleges. This chapter also indicated the study's research questions, null hypotheses, and methodology.

Chapter 2 includes an extensive review of the literature associated with pertinent topics related to DE programs, modality, placement, and student success. Chapter 2 also includes a thorough explanation of how Simon's (1947) bounded rationality theory provided the theoretical foundation for identification of the variables (i.e., student success, placement, and modality) and supported the research questions.

Chapter 2: Literature Review

This study researched the problem of low success rates among students in online DM courses. The purpose of this quasi-experimental quantitative study was to examine whether a change in UCCCD policy and practices for student placement into online DM courses could improve predicting the likelihood of student success. A review of relevant primary and seminal literature was used to establish the relevance of the problem.

The current researchers concurred that nationwide between 60% and 70% of freshmen community college students require academic support in at least one DM or English course (Center for Community College Student Engagement, 2016; Melguizo et al., 2016; National Center for Public Policy and Higher Education, 2010). To address this phenomenon of increasing numbers of academically underprepared students, community college leaders have increased the number of online DM courses. However, the low student success rate (62%) in online DM classes has only added to the challenge for community college leaders (Jaggars et al., 2013).

Fulton (2012) concluded that effective placement policy and practices can "either eliminate or significantly reduce the time students spend in developmental courses" (p. 6). The cost of remediation is high for both the students and the college, and the lack of effective policy and practices for placement into DM courses has consequences (Fulton, 2012). Abraham, Slate, Saxon, and Barnes (2014) reported that these consequences include the prevention of educated adults (a) entering the workplace, (b) participating in a community's economy, (c) fulfilling their life's goals, and (d) closing the lifetime earning's gap between high school and college graduates. Hence, Fulton (2012) concurred that an ineffective placement policy indicates that students often lack access to the information they require to not only transition to a postsecondary institution, but also make decisions about their future. This study's contribution to social change was to provide research data and findings that could be used to improve the placement policies and practices used to recommend modality of DM. As Simon's (1976) bounded rationality theory indicated, these improved policies and practices may assist students in making decisions about placement that are closer to being optimal.

Community college leaders continue to grapple with an increase in the number of students placed into DM courses and the low rates of student success in these DM courses, specifically online DM courses. In this literature review, I began with a restatement of the problem and purpose of this study, followed by a brief but concise synopsis of the current literature that established the relevance of the problem. A review of the literature search strategies follows. Next, I reviewed and provided rationale for the choice of the theoretical foundation for this study and for the selection of the study's key variables and concepts. Finally, I closed the chapter with a summary of the literature and identified the gap in the literature that my study addressed.

Literature Search Strategy

I accessed the following library databases and search engines to obtain information for this literature review: Google, Google Scholar, Educational Resource Information Center (ERIC), ProQuest Dissertation and Theses, ProQuest Center, Dissertations and Theses @ Walden, PsycINFO, and Sage journals, EBSCO Education Source. I also consulted the following public data sources: National Center for Education

Statistics and Community College Research Center. Searches were based on the following keywords: *developmental mathematics, remedial courses, underprepared students, placement tests, developmental mathematics persistence and retention*, *developmental mathematics withdrawal and dropout rates*, *reading comprehension in online education*, *ACCUPLACER,* and *Simon's bounded rationality theory*.

After an exhaustive review of the peer-reviewed literature and Walden dissertations between the years of 2014 and 2018, I determined that there was a dearth of research on the use of both reading comprehension and mathematics placement scores for determining the placement of community college students into DM programs. I also determined that there was a lack of studies on the link between reading proficiency and mathematics success in online DM courses. Saturation was achieved for this study by the use of peer-reviewed journals, books, national reports, and educational websites.

Theoretical Foundation

The purpose of theory is to provide researchers with a lens to explain a problem, to identify specific aspects of the problem, and to predict outcomes (Udo-Akang, 2012). DiMaggio (as cited in Udo-Akang, 2012) noted that a theory offers three views: the laws of the research field, enlightenment about a problem or phenomenon, or a narrative. My research does not set out to prove a theory. Instead, Simon's (1947) bounded rationality theory was used as a narrative to explain and predict the decisions made by community college leaders and students about student placement into online DM courses of basic arithmetic and introductory algebra. Additionally, the bounded rationality theory provided an understanding of why decision making is important in improving students' decisions about which modality of a DM course improves the likelihood of their success. The following subsections provided information on the theory's (a) origins, (b) major theoretical hypothesis and assumptions, (c) previous uses, and (d) rationale for choosing these theories as the foundation of this study.

Simon's Bounded Rationality Theory

Simon's bounded rationality theory indicated that organizations and people make decisions under the pressures (a) of time, (b) of incomplete information, and (c) of limited cognitive understanding (Hertwig & Pedersen, 2016; Polonioli, 2016; Simon, 1947). Simon's bounded rationality theory resulted from the author's interest in the literature on decision making (also known as heuristics) and the elements of cultural-cognition, which is also known as cultural capital (Simon, 1979). Simon (1947, 1979, 1982) recognized that institutions, as well as people, are often pressured to make decisions with incomplete information, limited cognition of the situation, and a finite time frame. Simon, as the seminal author of bounded rationality theory, concluded that organizational leaders and individuals, as decision makers, typically do not make the optimal choice, instead select the option that is both satisfactory and suffices or satisficing (Simon, 1976). The bounded rationality theory provided a view of how students, as decision makers, approach their selection of developmental courses modality. Also, the theory supported the idea that an institution needs to have policies and practices that provide the appropriate amount of information to facilitate student's decision making. By improving the information provided to students who require DM courses, students may make a more informed decision about a DM course modality that is closer to an optimal choice.

Origin of Bounded Rationality Theory

Simon's dissertation provided the impetus for the development of the bounded rationality theory (Puranam, Stieglitz, Osman, & Pillutia, 2015). Simon based his bounded rationality theory on the classical rational choice model of human decision making (Hertwig & Pedersen, 2016; Muntanyola-Saura, 2014). Before Simon's argument, economic theory (also known as the classical economic man) asserted that people made decisions that are optimal and rational and based on external constraints (Cowles, Deringer, Dick, & Webster, 2015). In contrast, Simon contended that cognition (an internal force), along with a lack of time and information, bounded or restricted people from making optimal decisions (Cowles et al., 2015; Simon, 1976).

Simon proposed the theory of bounded rationality in 1982, but coined the phrase bounded rationality in 1957 as an alternative view of a mathematical decision making model used in economics and political science (Cowles et al., 2015). Simon and Kaplan (as cited in Muntanyola-Saura, 2014) originated the definition of the cognitive process to include the notion that heuristics represented the core or essential element of organizational and managerial decision making. Hence, Simon's work can be found across a number of different fields of study that use organizational theories.

Theoretical Hypothesis and Assumptions

Simon's work focused on determining (a) an organizations' policy and practices, and (b) a person's behaviors that would support a decision that approached the best result

(Cowles et al., 2015). In support of bounded rationality, Cowles et al. (2015) remarked that it is both impractical and impossible to assume a person has access to all available and pertinent information prior to deciding. Bounded rationality theory indicates that policymakers are capable of focusing their attention only on the issues that relate directly to their area of responsibility (Cairney, 2014). Additionally, Cairney (2014) noted that policymakers' cognitive and information gathering abilities are limited. Carney (2014) and Polonioli (2016) agreed with Simon (1947) that decisions are based on a bounded decision making process that is further impeded by aspects of limited time, limited knowledge of the situation, and limited cognitive knowledge. Therefore, the decision making of community college policymakers and students would improve by providing timely and appropriate knowledge about the influence of the placement process and practices on success rates.

Previous Use of Bounded Rationality Theory

Bigsby, Ohlmann, and Zhao (2017) explored predictors of student athletes' decision making process about picking a college using Simon's bounded rationality theory as a framework for the study. Bigsby et al. contended that students' decisions about which school to attend were bounded by time, information, and cognitive resources. Similarly, bounded rationality framed a study conducted by Burkhardt, Smith-Coggins, and Santern (2016) that predicted medical residency students' interest in emergency medicine. Both studies concluded that students' educational decision making was bounded by the lack of time to decide, the lack of pertinent information, and the lack of understanding of the consequences of their decisions.

Scott-Clayton (2011b) observed that the literature supported the notion that community college students' persistence and success in programs is tied to a lack of structure and information that results in students making "less-than-optimal decisions" (p. *ii*). Diamond, Vorley, Roberts, and Jones (2012) similarly noted that higher education policy-makers needed to focus on how improving the information given students would improve students' decision making during the enrollment and placement period. Even though the authors of the previously noted studies did not always specifically mention Simon's (1947) bounded rationality theory, their findings and conclusions indicated that students, as decision makers, were bounded by their willingness to take a chance on a less than optimal solution. These previously mentioned authors also observed that students were bounded in their decision making by a lack of time and knowledge about situation, characteristics associated with bounded rationality theory. Similarly, my study examined student decision making during the placement process for DM courses. More detail on why students choose online over face-to-face can be found later in this chapter.

Rationale for Using Bounded Rationality Theory

Academically underprepared community college students often fail to understand the college environment or the consequences of their decision making (Saxon & Morante, 2015; Schneider, Sasso, & Puchner, 2017). The results of a study conducted by Schneider et al. (2017) at a midwestern university indicated that academic advising could be the key to success for students with limited knowledge or experience with postsecondary education. Many authors noted that postsecondary institutions' advisement counselors should promote the idea of how placement decisions can influence students' success, specifically to academically underprepared students requiring developmental courses and first-generation students (Miller & Murray, 2005; Schneider et al., 2017). In other words, several authors, previously noted, concurred that academic advisors are necessary to improve student decision making during the placemat process and improve student success. Both placement process and student success were elements that I analyzed for my study.

The bounded rationality theory indicates that not only academic counselors, as agents of the institution, but also students, as decision makers, do not have an accurate understanding of the complexity and structure associated with placement that guide policies and practices (Puranam et al., 2015). Miller and Murray (2005) concluded that during initial enrollment, underprepared students benefit from advising strategies that include (a) assessments (e.g., ACCUPLACER) that determine the student's skill and ability levels, (b) recommendations based on skill levels for appropriate courses with multiple options (time of day and modality), and (c) suggestions that cautiously recommend online courses. Miller and Murray, as well as Puranam et al. (2015) concurred that students require assistance with decision making as the result of their lack of receiving structured information, low cognitive understanding of the situation, and time pressures, that can occur during the academic advising of the underprepared student. Therefore, the use of Simon's (1947) bounded rationality theory seemed appropriate for my study, because the theory provided a framework to view student decision making during the placement process.

Literature Review Related to Key Variables

Having a high school diploma does not always mean being college ready. Almost 70% of freshmen community college students require developmental courses in reading and/or mathematics and less than half of these students successfully complete a DM course the first time (Center for Community College Student Engagement, 2016; Melguizo et al., 2016; Snyder & Dillow, 2015). Snyder, de Brey, and Dillow (2016) and McFarland et al. (2017) reported that more community college students require DE than students attending public doctoral degree granting universities. Hence, it seems important to examine the phenomenon of the academically underprepared community college students who require DE courses.

This phenomenon is not a new topic in the research literature. Effectiveness of DE programs, student and institutional predictors of student success, and misplacement of students into DE courses are the focus of researchers' interests (Chen, 2016). To ensure that this literature review represented current literature on the key variables, constructs, and concepts of this research, I organized this part of the literature review into sections. Each section represented key constructs, concepts, and/or variables. These sections include a wide arrange of topics (e.g., community colleges, college readiness, and developmental education programs) that represent the literature that built the foundation for this research.

Community Colleges

Community college faculty and staff provide postsecondary educational opportunities for a diverse group of learners who otherwise may not have access to college (Ginder, Kelly-Reid, & Mann, 2017; Quarles & Davis, 2016; Silver-Pacuilla et al., 2014). Students typically attend community colleges to prepare for jobs and careers in a changing global economy because these postsecondary schools provide workplace skills training that leads to certification, as well as provide a pathway to 4-year degree granting educational institutions (Davidson & Petrosko, 2014; Ginder et al., 2017). Millions of adult learners at community colleges have access to an education which in turn can act as a catalyst for personal and community economic growth (Ginder et al., 2017; Silver-Pacuilla et al., 2014). Baker & Levin (2017) added that community colleges promote affordable social mobility among first-generation college students, career changing adults, traditional, and nontraditional students. In other words, students, of all ages, attend community college because they want to improve their personal lives and economic futures.

In 2015-2016, nine million students made the decision to become students at a community college (Ginder et al., 2017). Additionally, 49% of the students who earned a bachelor degree in 2015-2016 had previously attended a 2-year institution (National Student Clearinghouse Research Center, 2016). The literature supports the idea that students are choosing community colleges to improve their economic future.

College Readiness

The National Forum on Education Statistics (2015) defined college readiness as "a student who has attained the knowledge, skills, and disposition needed to succeed in credit-bearing (non-remedial) postsecondary coursework" (p.vi). Researchers reported the importance of identifying the pathway to college readiness during the K-12 years, because this knowledge could stem the rise in the need for postsecondary developmental education courses (Cratty, 2014; Dougherty, 2014). Dougherty (2014) reported that a large body of literature indicated a consensus on the notion that college readiness begins in middle and high school. On the other hand, Cratty (2014) and Chapa, Galvan-De-Leon, Solis, and Mundy (2014) suggested that college readiness actually begins in third grade. While researchers may disagree on when college readiness begins, these same researchers agree that the lack of college readiness occurs sometime during the K-12 years.

Regardless of when students are identified as academically ready for college, the fact is that two-thirds of the students who enter community college are not prepared for college-level courses, specifically in mathematics and English (Bailey & Jaggars, 2016; Jaggars et al., 2015; Kim, Kim, DesJardins, & McCall, 2016). Knowing that college readiness beings and continues during the K-12 years allows for the foundational understanding that connects college-readiness to the constructed variable (summation of the reading comprehension and mathematics placement scores) of this research.

Measuring academic readiness and placement into developmental education courses was fully addressed in the placement section of this literature review. The following section describes ways that researchers of DE courses have approached improving student success in developmental courses. In addition, these approaches were analyzed for their strengths and weaknesses.

Developmental Educational Programs

Students, who are not college-ready, are often required to enroll in DE courses (e.g., mathematics and/or English) that are not credit-bearing (Bailey & Jaggars, 2016). Developmental education policies and practices are written to support those students who lack academic preparedness for college-level courses (Valentine, Konstantopoulos, & Goldrick-Rab, 2017). The terms developmental and remedial often are used interchangeably to describe non-credit bearing courses (Silvernail, Batista, Sloan, Stump, & Johnson, 2014). Typically, DE programs offer a series or sequence of courses designed to give academically underprepared students the knowledge and skill in mathematics, reading comprehension, and/or writing that prepares them for college level courses (Asmussen & Horn, 2014). For this study, the term developmental was used to describe courses designed to improve students' academic skills to prepare them for college-level courses in mathematics and reading comprehension.

Redesigning DE Courses

Many community college leaders continue to explore changes that would improve the outcomes for students in DE courses due to low student success rates in DE courses (Bailey & Jaggars, 2016). Post-secondary educational leaders in California, Florida, and North Carolina have modified their placement policies and practices to included multiple measures or have eliminated developmental courses (Saxon & Morante, 2015). Boatman and Long (2018) argued that students in DE reading are likely to also be enrolled in a DE mathematics and/or writing courses, which prolongs students time and increases costs for these students. As a result, community college leaders in several states are redesigning their DE courses.

Two designs, compressed and accelerated, have emerged to minimize the time students must spend on the DE trajectory to a college-level course. Compressed courses combine the content of multiple courses into one course, while accelerated courses can be completed within one semester or quarter (Saxon & Morante, 2015). Other community colleges are trying a co-requisite model where students enroll in a college-level course and a DE support course that is specific for that college level course (Boatman & Long, 2018). Researchers are just beginning to examine the effectiveness of these different approaches.

Using a quantitative methodology with linear regression analysis, Jaggars et al. (2015) examined community college DE accelerated programs. They concluded that accelerated strategies could reduce the attrition rate of underprepared math students, but not in a substantial number. As the redesigning models are new, Saxon and Morante, (2015) suggested the need for additional longitudinal studies before a definitive decision can be made about the effect of these changes on student success in DE courses. In other words, redesigning DE programs may not improve student success or student attainment.

Measuring Student Success in DE

Measuring student success at community colleges is difficult due to the open enrollment policy, which encourages a student population with varied levels of preparedness for college (Ireland, 2015; Saxon & Morante, 2015). The definition and measurement of success differs based on a stakeholder’s role and contributes to the lack of consistency among community colleges' measures of success. These measures of success include persistence, completion rates of DE sequence, transfer rate, degree completion, or completion time for a specific DE sequence (Ireland, 2015; Rehak & McKinney, 2015; Saxon & Morante, 2015). Boatman and Long (2018) noted that one of the goals of DE programs is the students' completion of college-level courses that lead to a college degree; thus, this is a common measure of success within the research community. This research defined student success as a final course grade for each of the two DM courses as an A, B, C, or P. These final grades make the student eligible for the next DM course or a college level mathematics course,

Findings on Student Success in DE Programs

Student success and placement policies are the focus of many DE research efforts. Many researchers of DE courses examine the effects of placement cut scores on predicting student success in these courses using regression discontinuity (RD), which is a standard statistical tool used with marginal cut score (e.g., -5 to +5 points of placement into a college level course instead of a developmental course) research (Moss, Yeaton, & Lloyd, 2014; Scott-Clayton, Crosta, & Belfield, 2014). The limitations of research that uses RD are that the authors focus on students who almost placed into a college level course, full-time students, traditional students, and recently graduated high-school students (Bohlig et al., 2018; Xu & Dadgar, 2018). The authors of these studies provided information about cut scores and placement into DM courses that expanded the foundational base for my research.

Valentine et al. (2017) conducted a meta-analysis of 11 studies that used 21 different settings, but similar samples. This meta-analysis answered the question of what happens after a student successfully completes the DE course required prior to enrolling in a college-level course. The studies reviewed data from 2006 to 2015, focused on DE students' who had placement scores (e.g. ACCUPLACER, ASSET, or COMPASS) within a few points on either side of the cut score (marginal cut scores) for a DE level and a college-level course. These researchers examined student success using a variety of factors, that included a comparison between students' who were required to take a DE course with those who were not required, the number of credits student earned previously, course completion where remediation was first required, and attainment. The results indicated that three years after completing the DE course students had (a) 3 credits less ($p = .002$), (b) had a final grade that was 7.9% points lower (75% to 68%, $p < .001$), and (c) had a 28.5% ($p = .03$) for attainment. Valentine et al. (2017) observed that more than three-fourths of the reviewed studies indicated a statistically significant negative result for students who find themselves referred to a DE course, which then requires more time to complete college-level courses and attain a certificate or degree. Hence, enrolling in a DE course had a negative social change influence, as this placement hindered students from their meeting educational and life goals.

A study conducted by Scott-Clayton and Rodriguez (2015), using data from an unnamed large urban community college district, indicated similar conclusion as Valentine et al. (2017). Scott-Clayton and Rodriguez concluded that placement into DM courses negatively affected success in the first college-level mathematics course and attainment. Even with similar findings, the previously noted researchers recommended a continuation of research on placement policies and practices

Acosta et al. (2016), along with Wolff et al. (2014) used logistic regression to study course modality along with other predictors of student success. Logistic regression requires a dichotomous outcome (dependent) variable and indicates to researchers a view of how predictor (independent) variables (categorical or continuous) are related to a dichotomous outcome variable (Field, 2011; Osborne, 2015). Osborne (2015) also noted that logistic regression provides the researcher with results that support policy and practice changes. Osborne's statement lends support to the theoretical framework (Simon's (1947) bounded rationality theory) of this study, as findings based on logistic regression testing can suggest changes in the placement's policy and practices that include information that improves students' decision making about whether online or face-to-face meets their academic needs and goals.

Boatman and Long (2018), using regression discontinuity analysis (RD) to analyze longitudinal data from Tennessee state community colleges, found that DE courses had a negative effect on students who needed only one DE course. Boatman and Long's findings were, however, positive for students needing more than one DE course. A weakness of this study was the sample criteria only permitted full-time students, which may or may not represent a typical community college DE population. Similar to my study, Boatman and Long included all students and a range of cut scores, instead of those students with marginal placement scores. Boatman and Long concluded that student success depended on the student's level of need (i.e., the number of DE courses required) for academic improvement in each of the areas of mathematics, reading comprehension, or writing. Boatman and Long found that students who required two DE courses in reading and writing were more likely to persist and attain a degree than similar students who only required one course in reading or writing. The findings of the Boatman and Long research contributed to my decision to include reading comprehension placement scores as a part of the placement predictor variable and to include all DM students, not just those students at the margin of the cut score between a DM course and a college level course.

While Boatman and Long (2018) and Scott-Clayton and Rodriguez (2015) had similar conclusions about student success in DE courses, Hodara (2015) reported contrary findings. Hodara (2015), using longitudinal data (10 years) from an urban community college and a difference-in-differences method, reported that students in the lowest levels of DE courses (both math and English) had a greater likelihood of not being successful in subsequent DE course. Boatman and Long observed that research findings typically are negative towards the effect of the DE courses on students' successful completion of a DE program's sequence of courses and attainment of degree or certificate. However, Boatman and Long argued that successful completion of a DE sequence is critical, as across this country there is a vital need for educated and skilled workers. Therefore, studies such as mine, contribute to the literature on DE and student success.

While most researchers of DE success and placement used regression discontinuity analysis, other authors had similar results with other statistical methods and theoretical lenses. Clotfelter, Ladd, Muschkin, and Vigdor (2015) used an instrumental variable strategy that had regression predictive power. These authors used placement policy when they conducted a study using data form a North Carolina community college. Clotfelter et al. (2015) asked whether 17,000 community college students had a chance for success when measured by earning a passing grade in a college-level course after a DE course. They reported that only 28% of students who took a DE course would pass a college-level course. These results added evidence that little improvement has been made in increasing DE students' success or acquisition of academic skills needed to succeed in their first college-level course.

Implications for DE Policies and Practices

Hodara and Xu (2016), after a review of the literature, concluded that currently there is minimal evidence that DE improves student success rates. As a result of similar findings, many state legislatures and community college leadership are in the process of redesigning their DE program. These changes are meant to increase student success, but Boatman and Long (2018) reminded community college leaders that it is crucial for them to remember policy changes within a DE program need to identify the specific academic needs of the student. College leaders, as policy and decision makers, are increasingly becoming aware that DE programs need to address DE students' varying levels of academic need (Boatman & Long, 2018). However, Scott-Clayton and Rodriguez (2015) questioned DE policies that seem to discourage or divert students who are not college-ready instead of developing or encouraging these students. In fact, Scott-Clayton and Rodriguez boldly stated that for many colleges, placement into a DE course was a diversion from college-level courses.

In support of the Scott-Clayton and Rodriguez (2015) statement, Hesser and Gregory (2015) added that first-time community college students often not only lack the academic knowledge and skills to be successful, but also lack an understanding of how to navigate the system and process information. Similarly, Galindo, Castaneda, Gutierrez, Tejada Jr., and Wallace (2015) commented that first-time community college students' lack awareness of their gaps in knowledge and skills associated with being successful in college; therefore, they require more support. Boatman and Long (2018) urged community college leaders to look at micro level (institutional) data, as well as enrollment decisions made during a student's progression through a DE sequence. College leaders also need to ensure that their DE policy and practices support not only a college's definition and measurements of student success, but also link DE student success (e.g. online DM students) with the college's mission and vision statements (Cafarella, 2014; Ireland, 2015). The conclusions posited by these authors lent support to my use of Simon's (1947) bounded rationality theory as the theoretical framework, because this theory addresses decision making at the leadership and student levels.

Cost of Developmental Education

The Century Foundation's College Completion Series indicated that four billion dollars per year are required to support developmental education (DE) programs (English and mathematics) and to assist academically underprepared students to gain the skills and knowledge required for successful completion of college-level courses (Bailey & Jaggars, 2016). Community college administrators are not the only individuals spending money on developmental education courses. Numerous researchers have stated that students in

DE programs are not only spending additional money, but also spending additional classroom time, as much as five years, to attain their education and academic goals (Crisp & Delgado, 2014; Fong et al., 2015; Ngo & Melguizo, 2016; Xu & Dadgar, 2018). The cost only increases when underprepared students choose online courses that have a high rate of failure and withdrawals when compared to face-to-face courses (Jaggars et al., 2013). The academic remediation of underprepared students is expensive, but failure to provide this academic assistance limits these students' opportunities for a college education and employment opportunities (Xu & Dadgar, 2018). However, numerous researchers consistently disagree on the effectiveness of DE programs (Jaggars & Stacey, 2014; Rodriguez et al., 2015; Xu & Dadgar, 2018). This lack of consensus about the effectiveness of DE programs provided the rational for continued research on DE programs.

Many authors have suggested that improving success rates of DE should begin with the placement process, but they also recognized that costs of DE programs would be increased with changes in the placement process (Rodriguez et al., 2015). Rodriguez et al., (2015) relied on the ingredients method to estimate the costs of placement, after DE policy changes, would be $300,000 to $875,000 per college with 60% paid by the college and the remaining 40 % by students. This 40% includes the cost of a student's time spent on the placement process as the result of the loss of wages, the cost childcare, and other responsibilities (Rodriguez et al., 2015). The authors not only noted the cost of changing placement policies and practices, but also noted that the cost of placement testing was considerably lower when compared to the cost of remediating students' academic skills in DE courses.

With a price tag of four billion dollars per year, community college leaders should expect an improvement in student success rates in developmental education courses as the cost of developmental programs for both community colleges and students appears to be substantial. However, the results do not support this supposition (Bailey & Jaggars, 2016; Chen, 2016; Rodriguez et al., 2015). Bailey and Belfield (2015) remarked that a student with a community college associate degree earns at least $5400 more each year than a student who dropouts. In 2016-2017, the average yearly cost at a community college was $3520, which is considerably less than the average yearly cost of $9650 at a 4-year college (Ma, Baum, Pender, & Welch, 2017). Bailey and Belfield concluded that the earning gains far exceeded the cost of a community college degree. While these authors argued that the initial cost of community college had a positive long-term effect, Hodara and Xu (2016) disagreed.

Hodara and Xu (2016) noted that most DE studies examined how DE influenced student outcomes. Instead, Hodara and Xu studied whether DE provided any benefits for students who started in a DE program but did not attain a certificate or degree. Using a fixed effects model, Hodara and Xu examined the academic transcript and employment records of students from 23 community colleges located in Virginia and determined that developmental English courses had a positive relationship with labor market productivity (potential earnings and likelihood of employment), while DM decreased market productivity. More importantly, these findings on market productivity indicated that older students had fewer positive results with DE English courses and more negative results for DM s courses (Hodara & Xu, 2016). This means that placement policies and practices have a long-lasting effect on students' future employment and financial success, specifically for students who require DM courses may experience lower potential earnings and less likelihood of employment. My decision to focus on placement as a variable for this research seemed appropriate and supported the idea that improving the placement process represented positive social change.

Mathematically Underprepared

This next part of the literature review section described ways that researchers have approached the problem of low student success rates in DM courses. Also included in this section are the description of DM programs and students in those programs, efforts to improve student success, and the redesigning of DM programs/courses to improve student success. Strengths and weakness of different approaches are also addressed.

Being mathematically underprepared is defined as a "student whose academic skills fall below those skills needed to be successful in college math" (Dzubak, as cited in Rhodes & Kramer, 2011, p. 1). The Institution of Educational Statistics (IES) organization indicated that 39% of the 2013 graduating high school seniors were academically ready for college, while only 26% of the 2013 graduating high school seniors were academically ready for college mathematics (National Forum on Education Statistics, 2015). Crisp and Delgado (2014) reported that the characteristics of students referred to DM courses are different than those students referred to college-level courses. These differing characteristics included academic preparation and experiences in high school, lower high school GPA, and fewer advanced high school mathematics courses (Crisp & Delgado, 2014). Therefore, being mathematically unprepared is the result of academic choices and decision making during high school.

Robinson (as cited in Bol, Campbell, Perez, & Yen, 2016) noted that underprepared mathematical students often fall into one or more categories of academic, emotional, and cultural unpreparedness, in which one or all could create a barrier that prevented success in DM courses. Mathematically underprepared students often over estimate their mathematical skill level, which tends to prevent them from (a) setting realistic goals, (b) navigating the institutional setting, and (c) asking for help (Bol et al., 2016). In addition, affective aspects (e.g., self-perception, confidence, attitudes and beliefs, and anxiety) influence student success in DM courses (Benken, Ramirez, Li, & Wetendorf, 2015). The conclusions on student success drawn by these previously noted authors are supported by the tenets of bounded rationality theory, which indicates that student characteristics prevent students, as decision makers, in making optimal decisions about their education.

Benken et al. (2015) collected primary survey data from 376 students in a California community college DM course to determine common characteristics among these DM students. Benken et al. (2015) found that even with four years of high school mathematics courses, about two-thirds of their study's participants required DM. More striking was the fact that 20% of these students successfully completed high school calculus. The authors of this study failed to identify clearly their sample, but the results indicated a focus on recently graduated high school students. The results from this mixed method study indicated that 60% of the students had taken high school courses beyond algebra 2 (i.e., statistics, precalculus, or calculus), while 23% of the students retook high school algebra 2 three or four times before passing the course. It was interesting that 21% of the students had completed a high school AP statistics or calculus course yet required a DM course. Benken et al. (2015) reported survey results that indicated most students in the study did not like mathematics, but 83% of them had confidence that they had average mathematical skill and would pass the DM course. Additionally, results indicated that 63% of the DM students studied less than four hours per week, considerably less than the mathematics faculty's recommendation of three hours of studying per one hour of class time (Benken et al., 2015). The authors concluded that for DM students completing four years of high school created a false sense of mathematical skill and failed to prepare them for college-level mathematics (Benken et al., 2015). Once again, student success in DM courses was linked to students' bounded decision making about their mathematics education.

Taking a different approach, Okimoto and Heck (2015) suggested that Tinto's academic integration model provided the foundation for improving student success in DM courses, by showing engaged students are more likely to be successful. Similarly, Davidson and Petrosko (2014) noted Tinto's framework for retention identified the variables, used in their study of persistence predictors for DM students. Goodman, Melkers, and Pallais (2016) used human capital theory to examine access to post-secondary education online courses and argued if online courses should be restricted to students with the academic skills and knowledge to improve student success. While my research used Simon's (1947) bounded rationality theory as a framework, other researchers have used human capital theory. For instance, Huntington-Klein, Cowan, and Goldhaber (2015) used human capital investment and consumption value to examine the relationship between the effectiveness of an online course and decision to take an online course. All of these studies mentioned above viewed student success in DM courses using other theories, not Simon's bounded rationality theory.

In contrast, Bol et al., (2016) posited that students in DM courses lack cultural capital, which prevented them from realizing how unprepared they were for college. Students, ranging in age from 17 to 50, reported that they did not realize the importance of the placement test and might have reviewed prior to taking the test had they known. Bol et al. (2016) argued that this lack of cultural capital explained many of the survey results. Valdez (1996) explained that cultural capital referred to the "linguistic and cultural knowledge of how a system works as a result of the social location of one's family" (p. 393). The notion of a lack of cultural capital is an aspect of Simon's bounded rationality theory's that indicates a lack of cognitive understanding of how a system works contributes to choosing a satisficing solution instead of an optimal decision (see Simon, 1957). While cultural capital is an important aspect of student decision making, this research did not address specifics of cultural capital that influence the student placement process or its influence on online DM courses. Instead, my research focused on students' decision making and how it is bounded by time and lack of information. In addition, students lack understanding on how post-secondary education functions (cultural capacity) was also considered. Hence, students in DM courses often lack skills beyond the academics that contribute to them not being college ready or underprepared.

Nationwide the number of underprepared community college students continues to increase, especially in mathematics (Kim et al., 2016; Jaggars et al., 2015). In Arizona, less than half of the 2014-2015 high-school graduates were college-ready (Paquest & Harper, 2015). Students who arrive unprepared for college level courses need a longer time to meet mathematics course requirements and may have to repeat DM courses, which could delay meeting their education goal of a certificate or degree (Benken et al., 2015). In addition, Fong et al. (2015) argued that previous studies identified math ability as a significant predictor of student success. Benken et al., (2015) found that students who had to deal with any form of delays in their education would forgo degree programs that required mathematics. Therefore, the result of being underprepared in mathematics leaves these students with fewer program options.

As previously noted, successfully completing a DM course sequence is no guarantee of success in college-level courses or attainment of a college degree. Quarles and Davis (2016), using regression analysis, reported that the standard focus of DM courses is procedural skills and not the application of skills, which does not ensure a successful outcome in a college-level mathematics course. Using a *t*-test with no other explanation of the method, Parker et al., (2018) rendered the same conclusion as previously noted authors that successfully completing a DM sequence does not always indicate students can apply their algorithmic learning to college-level mathematics. Therefore, students who are underprepared for mathematics not only lack academic skills and knowledge, but also lack cultural knowledge, both of which contribute to low success rates in DM courses.

Developmental Mathematics Programs

A DM course sequence typically includes courses in basic arithmetic, introductory algebra, and intermediate algebra, with a student's first course dependent on their placement score (Ariovich & Walker, 2014, p. 46). Only 30% of DM students typically complete a required sequence, which may span multiple semesters if students fail or withdraw (Ariovich & Walker, 2014). To increase student success and degree attainment and to reduce the external stakeholder pressure, community college leaders have begun experimenting with alternative models of delivery, but many of these changes were never fully adopted (Kosiewicz, Ngo, & Fong, 2016). Regardless, community college leaders continue to explore ways to improve student success rates in DM.

Student success in DM courses has also become a focus of community college leaders due to pressure from the federal and state governments to justify the investment in DM (Ariovich & Walker, 2014; Wolfle & Williams, 2014). Rehak and McKinney (2015) reported that numerous changes had been proposed at the national, state, and institutional level with the goal of improving success rates in DM programs. However, after a decade of changes made in at least 200 colleges, little improvement in student success has been reported. Researchers have posited whether changing DM policies and practices would increase student success rates in DM courses, thereby increasing students' attainment of goals (Fong et al., 2015). While many researchers argued for the need to make effective changes in DM courses to improve students' chances of obtaining their academic and life goals, Bol et al. (2016) reported that there is no research that indicates any changes that made an overwhelming difference for students in DM courses.

Rationale for Selecting Variables

In the following section, I justify the rationale for the selection of placement scores for reading comprehension and mathematics, modality (online and face-to-face), and student success as variables for this research. I also review and synthesize studies related to the key variables to provide a description and explanation (background) of what is known about the selected variables. Additionally, I describe studies related to the methods of my research, specifically the use of ex-post facto data and analysis using binary logistic regression.

Reading Proficiency and Mathematics Learning

One of my concerns with selecting reading comprehension as a variable for this study was the limited number of studies at the community college level. However, the K-12 literature provided ample research that supported my selection of reading comprehension and its influence on mathematics achievement. Fong et al. (2015) used research from the K-12 literature to justify their use of community class size as a variable. My research also relied on research from the K-12 literature to justify the selection of reading comprehension as a variable.

An analysis of student data (Grades 3-11) from 37 countries, Nortvedt et al., (as cited in Nilson & Gustafsson, 2016) concluded that reading facilitates students' access to mathematical learning. Likewise, after examining the effect of reading proficiency on community college student learning, Xu (2016) concluded that students' low reading proficiency negatively influenced their success in other developmental education courses, which included writing and mathematics. Many researchers within the K-12 domain used a variety of measurements and concluded that a relationship existed between a student's reading proficiency and mathematics achievement. A longitudinal study of students in Grades 3-11 using a statewide assessment tool revealed a strong relationship (correlation of 0.90) between mathematical achievement and reading (Adelson et al., 2015). Similarly, researchers, using the results of TIMSS 2011 and PIRLS 2011, determined that at the fourth-grade level the correlation between reading proficiency and mathematics achievement was .90 (Nortvedt et al., as cited in Nilson & Gustafson, 2016). These previously noted researchers agree that a link exists between reading proficiency and mathematics achievement in the K-12 years, but have not extended that link to the college years. My study extended this link to community college students in DM.

Adding to the body of literature concerning the link between reading proficiency and mathematics achievement, authors at the National Forum on Education Statistics (2015) reported a strong relationship exists between mathematics achievement and reading proficiency for 15-year old students. The Lemke et al., (2004) report indicated two scenarios with 15-year old students: (1) students who scored below average on the PISA 2003 test in reading also scored below average in mathematics or (2) students who scored below average in mathematics also scored low in reading. The authors of the Lemke et al., (2004) posited that a link exists between reading proficiency and mathematics achievement of all students, regardless of age.

Fike and Fike (2008) reported a possible link between students' success in college (2-year or 4-year) and their reading proficiency, but the authors made no direct link between reading proficiency and success in DM courses. After analyzing data from over 200,000 students from 107 California community colleges, Bahr (2010) reported that reading proficiency influenced DM students' successful remediation in mathematics. Bahr, along with Fike and Fike (2008), concluded that students' inability to read and understand college textbooks contributed to a lack of success in DM courses. Consequently, students with both reading and mathematics academic deficiencies are less likely to complete a DM course sequence successfully (Bahr, 2010). Bailey (2009) examined more than 250,000 freshmen students from 130 different community colleges and reported that 34% required developmental reading. Similarly, Adelman (2004) reported that two-thirds of students in developmental reading courses subsequently enrolled in other remedial courses (i.e., mathematics and writing). According to Cox, Friesner, and Khayum (2003), a number of authors have reported a positive correlation between student persistence in college that could indicate success in mathematics courses and student success in developmental reading courses. However, Fike and Fike noted that further research was needed to determine whether a relationship existed between reading proficiency and student success in DM courses.

The link between reading proficiency and mathematics achievement has also been established using state, federal, or international assessments. Ercikan et al. (2015) examined the 2009 PISA results for 15-year-olds and concluded that reading proficiency and mathematics performance have a strong relationship. In fact, reading proficiency accounted for 43% of the variance reported for mathematics scores on the 2009 PISA (Ercikan et al., 2015). Earlier, Lee and Spratley (2010) reported that struggling readers have difficulty with both the reading of mathematics textbooks and the learning expected from reading mathematics textbooks. Developers of the University of Chicago School of Mathematics Project (as cited in Lee & Spratley, 2010) also reported that students who cannot independently read a mathematics textbook are unable to learn mathematics outside the classroom. An assumption could be that students require developmental reading courses because they lack the reading proficiency and independent reading skills necessary to complete an online mathematics course, specifically an online DM course.

Survey results of over 9000 K-16 teachers conducted by ACT National Curriculum Survey indicated that teachers within the K-12 system needed to increase the amount of time teaching specific reading comprehension strategies for mathematics to improve students' lifelong ability to learn mathematics (ACT, 2013). The authors of the ACT survey also concluded that by increasing students reading proficiency, students would be able to read and learn mathematics independently. In other words, the findings of the ACT survey could suggest that community college students' success in online mathematics courses (e.g. DM courses) requires strong reading skills that support the independent learning of mathematics that is required of online DM courses.

Jaggars (2014) confirmed earlier findings made by Jaggars and Xu (2010) that community college students reported that they selected online courses knowing that they would need to teach themselves. Again, this student view suggests an understanding of the expectation that an online course requires students to independently read and understand the mathematical content and its application to mathematical problems. On a social change point of view, Lee and Spratley (2010) added the importance of reading in the content-areas as it prepares adolescent readers for “citizenship, encourage personal growth, and life-satisfaction on many levels, and open up opportunities for future education and employment” (p. 2). Therefore, it is important for researchers to continue examining the influence that reading proficiency has on student success in online DM courses.

Kauffman (2015) found that not all students have the necessary skills to be successful in online courses and because of this fact, institutions needed to identify which student academic characteristics supported the successful completion of online courses, specifically reading. Kauffman indicated that students are expected to read independently online textbooks and support material that provide the structure for many online courses. Studies also indicated that instructors of online courses communicate through writing, which is an aspect of reading proficiency, while instructors in face-to-face courses judge students’ understanding of information through verbal and non-verbal communication formats (Berenson, Boyles, & Weaver, as cited in Kauffman, 2015). These authors agreed that reading proficiency should be a factor when students are deciding whether to enroll in a traditional DM course or an online DM course.

The findings suggest that reading comprehension is a predictive factor in not only students’ success in developmental courses, but also students’ success in completing academic goals. Even though researchers have assumed the existence of a link between a college student’s reading proficiency and academic content area success, the link between reading proficiency and online DM achievement (success) at the community college level is weakly explored in the literature (Xu, 2016). I identified this gap in the literature after an extensive Internet search returned a limited number of studies on a link between community college students' reading proficiency and their success in online DM courses.

Online as a Modality

A search of the literature indicated that while community colleges have increased the number of online learning courses, their effectiveness is questionable (Xu & Jaggars, 2011a, 2011b). According to the U.S. Department of Education's Integrated Postsecondary Education Data System's (IPED) data, 5.8 million college students enrolled in at least one online course in the fall of 2014. Since 2002, online enrollment has grown about 16%, which is substantially higher than the 2.5% annual enrollment rate in post-secondary institutions (Allen & Seaman, 2011). Kauffman (2015) and Bettinger and Loeb (2017) attributed this rapid growth in online courses to the fact that online courses offer students a convenient and flexible modality not available with face-to-face courses.

Online students often have personal responsibilities beyond academic needs that require a different format than the traditional face-to-face modality. The reported increase in the number of students in online courses has been attributed to the fact that modality offers a convenience to students (Kauffman, 2015). Some authors have posited that the increase in colleges and universities offerings of online learning is a result of pressure from non-traditional students needing a more convenient and flexible learning environment (Shukla et al., 2014). Jameson and Fusco (2014) also noted that a large and growing section of community college students are adult learners or nontraditional students, who, according to Hixon, Barczyk, Ralston-Berg, and Buckenmeyer (2017), are attracted to the flexibility of online courses. Similarly, results from a Ruffalo Noel Levitz (2016) survey of 118,322 online students in undergraduate and graduate courses, indicated that the top four reasons why community college students enroll in an online class are convenience (93%), flexible pacing (88%), cost (88%), work schedule (87%). These researchers also suggested that students typically do not consider the reading skills required to be successful in an online course, instead only focus on nonacademic factors.

Regardless if a student is traditional or nontraditional, the increase in community college enrollment has been attributed to students' desire for online courses and the need for developmental courses, specifically mathematics (Ashby et al., 2011). However, Zavarella and Ignash (as cited in Shukla et al., 2014) warned that course modality (learning environment) influences completion rates of students in DM course sequences. Shukla et al. (2014) observed a general decrease in performance among community college students taking online courses. The results of a one-year study conducted at Columbus State University indicated that the student success rate in online developmental courses (e.g., Developmental Math 1 and 2, and Preparatory Algebra) were lower by an average of 11% when compared to the face-to-face version of the same course (Shukla et al., 2014). These findings were verified by other authors.

A number of researchers reached the same conclusion that online courses, while providing students with convenience and flexibility, have a high withdrawal and failure rate, especially DE courses (Croxton, 2014; Jaggars, 2014; Jaggars et al., 2013; Xu &

Jaggars, 2013; Zavarella & Ignash, 2010). In addition, Acosta et al. (2016), after reading numerous DM studies, generalized that not completing DE courses was the result of students' weak academic proficiencies as well as the format of the DE courses format, specifically online. Similarly, the results of a study with 167 participants from a large Mid-Atlantic Community College indicated that student success in DM courses was significantly affected by the modality (online, blended, and face-to-face) with online student rates of success lower than the success rates for face-to-face when attrition was not a factor (Ashby et al., 2011). Xu and Jaggars (2014) conducted a study that involved over 40,000 community college students in Washington State's community and technology schools and concluded that a performance gap was evident when comparing face-to-face courses with online courses for all students. In other words, these previously noted authors reached a consensus that students in online courses had a lower achievement performance regardless of academic subject.

In contrast, using descriptive statistics and logistical regression analysis, Acosta et al., (2016) concluded that DM course modality had no effect on students' successful completion of a college level mathematics course. This result, according to Acosta, et al. (2016) was contrary to similar studies conducted by Croxton (2014), Jaggars et al. (2013), and Xu and Jaggars (2013, 2014) that determined modality was a significant predictor of student success. Xu and Jaggars (2011a) indicated that DM students had difficulty in online courses, which is contrary to other studies previously mentioned. The work of Xu and Jaggars (2011a) reported the value of the *F* test for the final grade was significant (p = .017) at the .05 level. Xu and Jaggars concluded that academically underprepared community college students had “difficulty adapting to online courses” (p. 18). Similarly, after evaluating the performance of 105 biology students, researchers, using logistic regression, determined that both mathematics proficiency and course modality had a negative effect and were significant predictors of student success (Wolff et al., 2014). This lack of consistency among researchers supported the need of my research.

In my study, students self-selected the modality of their DM course. Nguyen (2015) concluded that the literature had no clear indication that self-selection of modality was significant. For my study, the idea of self-selection of course modality was being examined.

Developmental Mathematics Course Placement

Almost all postsecondary institutions have a placement process, which includes placement tests and cut scores, for assessing incoming students for college-readiness (Fulton, 2012). The identification of students needing DM (i.e., academically underprepared students) varies among post-secondary institutions. Many community colleges use the results from ACCUPLACER, COMPASS, or ALEKS to determine if students have the academic skills needed to enroll in college-level courses in mathematics and English or require developmental courses (Scott-Clayton & Stacey, 2015; Ngo & Kwon, 2015). The UCCCD colleges have used the ALEKS and ACCULACER placement tests for the placement of students into developmental courses—reading, mathematics, and writing.

Fulton (2012) raised the concern that few postsecondary institutions (2- or 4-year) regularly reviewed the validity of their placement test. In the spring of 2014, UCCCD leadership adjusted the ACCUPLACER test's cut scores for both placement tests (arithmetic and elementary algebra) due to a decline in successful completion rates in the DM course for the Fall 2012-2013 school year. Due to the lower success rates, UCCCD academic leaders adjusted the mathematics cut scores to include students with somewhat higher mathematics skills, which result in improved success rates for students in DM courses. Fulton concluded that institutions needed to refine their placement policies and practices to ensure that students are accurately assessed and placed not only in the academically appropriate course, but also the most advantageous modality. UCCCD students placed into DM courses (basic arithmetic or introductory algebra) have the option of choosing among three modalities (face-to-face or online), but often without knowing the effect of their decision on their success as advising is limited.

Bailey (2009) recommended the need for additional studies on the placement process, which includes DM, due to the lack of consensus about placement policies and practices among community colleges and researchers. Jaggars et al. (2015) continued the debate by positing that low DE student success rates could partly be the result of placement errors due to institutions' placement policies and practices. My study explored a possible link between UCCCD's the placement policies and practices and student success. Between Fall 2014 and Spring 2017, UCCCD's placement practice was to use ACCUPLACER as its placement test.

ACCUPLACER as a Placement Instrument

Fulton (2012) noted that ACCUPLACER is used by a majority of community colleges and is touted by researchers as a good predictor of student performance in college-level courses. Fulton reported a concern among researchers as to the effectiveness of the College Board's ACCUPLACER as a predictor of placement into developmental courses. The writers of ACCUPLACER stated that their series of placement tests measure students' academic skills in mathematics, reading comprehension, and writing, as well as determine if developmental education courses are required (The College Board, 2018a, b). My research used the scores from the ACCUPLACER tests for elementary algebra and reading comprehension as predictors of student success.

ACCUPLACER placement program has three mathematics tests: arithmetic, elementary algebra, and college algebra. The arithmetic test measures a students' ability to perform "(a) operations with whole numbers and fraction, (b) operations with decimals and percent, and (c) applications and problem-solving" (The College Board, 2018a, p. 1). The elementary algebra test measures students' ability to solve problems using, (a) operations with integers and rational numbers; (b) operations with algebraic expressions; and (c) solutions of equations, inequalities, and word problems" (The College Board, 2018a, p. 1). The college algebra test measures students' ability to solve problems using "(a) algebraic operations, (b) solutions of equations and inequalities, (c) coordinate geometry; (d) applications and other algebra topics, and (e) functions and trigonometry" (The College Board, 2018a, p. 1). The reading comprehension test measures students' "ability to understand what [you] read, to identify main ideas, make inferences, and distinguish between direct statements and secondary or supporting ideas" (The College Board, 2018a, p. 1). The scores from the elementary algebra test and the reading comprehension test were used in my study.

The purpose of this quasi-experimental quantitative study was to examine whether a change UCCCD's policy and practices for student placement into online DM courses could improve predicting the likelihood of student success. The contradictory research results, as previously discussed, provide evidence and justify the selection of modality, reading comprehension, mathematics proficiency, and student success as variables for this study.

Misplacement of Students in Developmental Mathematics Courses

Many authors have noted a concern with a single placement test for course placement due to concerns about students being misplaced into either college-level courses or developmental education (DE) courses (Fulton, 2012; Scott-Clayton et al., 2014). Bailey (2009) also noted that much of the research focused on the effect of the placement cut scores as researchers examined if arbitrary cut scores truly indicated which students required DE courses and those who were college-ready. However, students with very low placement scores were often not included in the studies as there was limited research data on students with low placement scores who went on and completed college-level courses (Bailey, 2009). This was not the only concern noted by authors.

A second concern raised by many authors was the misplacement of students into DE courses. Studies indicated that a third of incoming community college students are mistakenly placed into DE courses due to their placement scores (Scott-Clayton et al., 2014). This misplacement is attributed to inadequate placement policies (Fulton, 2012). Some authors concluded that misplaced students spend additional time and money in courses that that did not meet their academic needs (Scott-Clayton et al., 2014). Likewise, Hodara and Xu, 2016 reported that misplacement created a situation where students' labor market outcomes are diminished.

A third concern focused on students who had placement scores on either side of the cut score that separated a DM and a college level course. These scores are commonly noted as marginal cut scores. Bailey (2009) observed that students near (above or below) the cutoff score spent time and money on DM courses that research findings suggested were not effective for this group of community college students, while students just above may have benefited from DM courses. Bailey (2009) encouraged community colleges to relook at their placement process for DM courses, specifically for students who scores hover just above and below the cutoff scores. These three concerns have guided the more recent studies in DM education.

To reduce the misplacement of students, many community colleges are changing their placement process to include other measures to augment placement scores (Bracco et al., 2014; Dadgar, Collins, & Schaefer, 2015; Fulton, 2012; Scott-Clayton & Stacey, 2015). Dadgar et al. (2015) and Ngo, Kwon, Melguizo, Prather, and Bos (2017) suggested that multiple measures added to the placement process would reduce the number of misplaced students. These suggested measures included high school GPA, prior mathematics, and English courses. However, as multiple measures are a new placement process, there is limited research on whether this change has improved success rates in DM courses.

As previously noted, misplacement tends to occur at the margins of the cut score that separates the highest-level course in a DM sequence and the first college-level mathematics course. A number of studies suggested that high school grade point averages (GPAs) could be used to predict the appropriate level of course work (developmental or college-level) for new students who graduated from high school within one year of enrolling (Hodara & Xu, 2016). In a study of Alaskan high school students, grade point averages (GPAs) were not more predictive than ACCUPLACER mathematics placement scores when students delayed entry into college for a year (Hodara & Lewis, 2017). Unlike other studies that researched misplacement of students based on cut scores, my research focused on the placement scores used to refer community college students to both UCCCD DM courses. The results of my research provide community college leaders with information about using reading comprehension placement scores as an additional component of placement into both DM courses.

Studies Related to Research Questions

Many studies suggested adding demographic factors, high school transcript factors, social-emotional-motivation factors, but none indicated including a composite placement score. Bahr (2010) suggested that the level of deficiency (depth) and the number of areas needing remediation (breadth) represented two predictors of developmental education success. An extensive search of the literature failed to return any studies that included a composite placement score based on the reading comprehension score and mathematics placements score or just the placement scores for reading comprehension and mathematics. This lack of studies that examined the use of a composite placement score as a predictor represents a knowledge gap in the literature. The following section of the literature review is intended to examine and synthesize studies related to my research questions.

While there are two research questions, these research questions are identical in all ways except for the DM course that is the focus of the research question (RQ). RQ1 focused on students who attempted the basic arithmetic course, which is the lowest level of DM course offered at UCCCD. While RQ2 focused on students who attempted introductory algebra, which is the highest level of DM courses offered at UCCCD. Studies related to these research questions needed to address either a composite placement score and student success in online courses. A number of researchers used a variety of statistical methods to identify and examine institutional and student characteristics as factors that could predicted the grade on final exams or the likelihood of student success in DM courses. However, none of them examined student success in a single DM course, not a sequence of DM courses, nor did any of them us a composite placement score.

Korpershoek et al. (2015) used multivariate multilevel models to determine that reading comprehension and mathematical skill/knowledge related positively to final exam scores in pre-university mathematics courses. They reported a moderate relationship (0.09 to 0.30) among reading comprehension, mathematical skill/knowledge, and final exam grades. Nortvedt et al., (as cited in Nilsson & Gustafsson, 2016) analyzed

TIMSS 2011 and PIRLS 2011 data and reported that mathematics achievement was influenced by reading comprehension in Grades 4 and 11 in 37 different countries, which did not include the United States. They also reported that the correlation ranged from 0.824 to 0.996.

Similarly, Davidson and Petrosko (2014) reported the use of logistic regression to examine the relationship among factors that included demographic characteristics, academic factors, and work and family factors. The Davidson and Petrosko study concluded that academic factors (GPA and cumulative grade point average) and modality of the course were significant predictors of the likelihood of persistence. However, Davidson and Petrosko did not include data on modality. While each of these topics—student success, reading comprehension, mathematics, and modality—has been covered in the literature review, I could not find research that used a constructed variable based on combining placement scores of reading comprehension and mathematics proficiency (a composite placement score). Hence, this lack of research on the effect of a composite placement score on student success in online DM courses represented a gap in the research literature.

Summary and Conclusions

In Chapter 2, I presented a justification for the need to continue the research on community college students' success in online DM courses. A number of authors pointed out that community college leaders continue to increase the number of online DM courses even in the face of a low student success rate and a high withdrawal rate. Simon (1982) explained that decision-makers (individual or organizational) are willing to make a less optimal decision are bounded due to a lack of adequate information, which makes their decisions bounded. Community college leaders often fail to provide a structure that encourages students to make decisions that are optimal to their persistence and attainment of a degree. The findings of my research provide community college leaders the impetus to begin the conversation on changing the placement policy and practices that dictate the type of placement information shared with students.

Numerous researchers, as previously noted, stated that community college administrators are augmenting placement policies and practices with holistic measures, such as high school GPA, full or part-time student status, and years since graduating from high school. However, few of these changes in the placement process have significantly increased student success in online DM courses. Much of the research findings indicated that students who take online DM courses are less likely to persist or attain a degree.

My research identified reading comprehension as a possible predictive factor in determining online DM student success. The results add to the literature by examining the role that a composite placement score has on predicting the likelihood of student success in online DM courses. My research examined student success in two DM courses and not a sequence or programs, which is a topic within the domain of DM not often covered in the literature. Chapter 3 provides details on how the quantitative research design (static-group comparison) and method of inquiry (logistic regression).

Chapter 3: Research Method

The purpose of this pre-experimental quantitative study was to examine whether a change in UCCCD's policy and practices for student placement into online DM courses could improve predicting the likelihood of student success in the courses. The major sections of this chapter include the rationale for the research design, methodology, and threats to validity.

Research Questions

The following research questions guided this study:

RQ1: To what extent does a combined placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course basic arithmetic where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, introductory algebra?

RQ2: To what extent does a combined placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course introductory algebra where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, intermediate algebra?

Research Design and Rationale

I used a pre-experimental static-group comparison research design. Additionally, I used binary logistic regression to analyze the historical data. The findings from this research extended or confirmed previously conducted quantitative studies that examined student success in community college DM courses, placement policies and practices, and modality (face-to-face or online). Logistic regression was used to examine relationships between a binary categorical outcome variable and a set of categorical and/or continuous predictor variables (Field, 2011).

A logistic regression model was appropriate for this research study because the outcome variable for both research questions was dichotomous (success or no success), and the study was predictive (see Conchran et al., 2014). Logistic regression supports a dichotomous outcome (dependent) variable and gives researchers a view of how predictor (independent) variables (categorical or continuous) are related to a dichotomous outcome variable (Field, 2011; Laerd Statistics, 2015; Osborne, 2015; Wuensch, 2014). Also, a logistic regression analysis contributes to building a model to predict the likelihood of an outcome (i.e., student success) based on chosen predictors such as placement scores and modalities (Fong et al., 2015). The results of the logistic regression analysis indicated whether the independent variables are significant statistical predictors of the outcome (student success), and the strength and direction of that relationship (Osborne, 2015). Liu and Jones (2015) stated that tests similar to the SAT, such as ACCUPLACER, are predictive of student successes. Hence, a logistic regression analysis model was an appropriate choice for this research as it provided results that indicated whether the variables statistically and significantly predicted the likelihood of student success in an online DM course.

Variables

For this research, the dichotomous outcome (dependent) variable for Research Questions 1 and 2 was student success measured by a final grade of A, B, C, or P, which means the student is eligible to enroll in the next mathematics course in the DM sequence or a credit-bearing mathematics course. Lack of success was measured by a final grade of D, F, W, or Y. A *Y* grade represents withdrawing but failing, whereas a *W* indicates passing at the time of withdrawing, but neither grade made the student eligible for the next course in the DM sequence or a credit-bearing course.

The continuous predictor (independent) variable for Research Questions 1 and 2 was the composite score, which represented a constructed variable created by summing the reading comprehension and mathematics ACCUPLACER placement scores (see Korpershoek et al., 2015). Modality was a dichotomous variable (online or face-to-face) for both research questions. The dichotomous dependent variable was student success measured by success or lack of success. Interactions between the predictor variables were also investigated.

Static-Group Comparison Research Design

I used a pre-experimental, static-group comparison research design, which is one of the quantitative research designs identified by Campbell and Stanley (1963). The pre-experimental, static-group comparison research design was used to examine how the change in modality (as a treatment) and a composite placement score influence student placement and success in an online DM course (see Campbell & Stanley, 1963). The following is a description of the pre-experimental static-group comparison model

(Campbell & Stanley, 1963). The model of the static-group comparison design research design indicates the need for a treatment (*X*), a treatment group (O_1), a control group (O_2), and additional factor that could also explain the change in the outcome (see Campbell & Stanley, 1963). For this research, the treatment group were the students in the online version of the DM course, while the control group were students in the face-to-face version of the DM course.

The static-group comparison design connected to the research questions as it did not require pre-/post testing and indicated the ability to determine the influence that a treatment (modality) has on student success. The research design also supported the addition of other factors (e.g. composite placement score). I chose a research design that supported a comparison between each group to determine if the treatment (X) affected the outcome (Campbell & Stanley, 1963). The static-group comparison design was appropriate for the research because the design supported my use of ex-post facto data and is frequently used in educational research (Campbell & Stanley, 1963).

Methodology

For this research, knowing the exact process used in collecting data was just as important as knowing that the process is uniform among the contributing district campuses. The UCCCD district stores student data for the purpose of conducting internal research. The following sections describe the details of the methods that were used for this research.

Population

The UCCCD community college district averages 128,000 students per semester of which 72% are part-time students and 28% are full-time students. The target population was UCCCD students who took the ACCUPLACER placement tests for reading comprehension and mathematics between August 1, 2014 to September 1, 2017 and placed into a DM course based on their ACCUPLACER mathematics placement score. The target population size for this study was 39,585 of which about 55% were female and 44% were male. The target population had an age range of 18 to 81, with 75% being between 18 to 25 years of age. UCCCD indicated that approximately 18,000 new students enter each term with about 65% of them needing DM. Of the targeted population, 42% enrolled in Basic arithmetic and 58 % enrolled in introductory algebra (see Table 3 in Chapter 4 for more details).

This quantitative study used a nonrandom convenience sampling strategy to identify potential participants in the targeted population. Etikan, Musa, and Alkassim (2016) described convenience sampling as a type of nonrandom sampling where the target population consisted of members who met certain practical criteria. A staff member from UCCCD's Office of Institutional Effectiveness drew a sample based on the sampling frame I provided.

Students who met the sampling frame were UCCCD students who (a) took the ACCUPLACER placement tests for reading comprehension and mathematics within two years of enrolling in a DM course; (b) enrolled in a DM course, either basic arithmetic or introductory algebra; and (c) received a final grade. Only students who had reached the age of 18 on or before August 1, 2014, were included, thus meeting UCCCD's Institutional Review Board requirements of not including participants who belong to the protected class of children. Students in the sample must have attended a UCCCD campus between the Fall 2014 semester and the Spring 2017 semester. Finally, students who took the placement tests before August 1, 2014 would be excluded due to the change in the placement test and cut scores. Students who withdrew from a course before the no-penalty drop date were not included in the sample and were removed from the data file by UCCCD's research department according to communications with the office. This decision was based on the work of Fong et al. (2015) who defined "attempt" as students who remain in a course past the college's no-penalty drop date (p. 732). Students who did not fit these criteria were excluded from this research.

Sampling and Sampling Procedures

Originally, I had intended to use the targeted population of about 40,000 students for this study. I ran a priori analysis, using G*Power 3.1.9.2, that indicated the need for a sample size of between 38 to 430 (depending on the odds ratio of small, medium, or large) for an α = .05 and power (1- β) = .95. G*Power is a power analysis program commonly used in social science research to calculate sample sizes based on significance level (α), the desired statistical power (1- β), and the determined effect size (see Faul, Erdfelder, Buchner, & Lang, 2009). As this research used nonprobability sampling and a large historical data set, I was not concerned about the need to conduct a power analysis. Due to the large sample size of this research, the significance level was α = .05 and power (1- β) = .95. However, after reviewing the data, I concluded that a stratified random sampling of the targeted population would best fit my study. More details regarding this issue are found in Chapter 4.

Formation of Samples for Each Research Question

This research had two questions each based on a specific DM course. Participants for each RQ were based on which DM course they attempted. RQ1 examined the likelihood of student success in basic arithmetic, while RQ2 focused on the likelihood of student success in introductory algebra. UCCCD placement policy requires all new (first time) students to take ACCUPLACER placement tests that include three different mathematics tests (arithmetic, elementary algebra, and college level) and reading comprehension. Students in this study typically self-selected the placement mathematics test and then enrolled in a DM course based on the results. However, as noted in Table 1, students had testing options if they did not like their course placement. Table 1 indicates student placement into DM courses based on the specific mathematics test score and options. As a reminder, participants need to have (a) taken the placement test for mathematics and reading on or after August 1 of 2014, (b) placed into one of two DM courses, basic arithmetic (MAT 08X) or introductory algebra (MAT 09X), and (c) attempted the course between Fall 2014 semester and Spring 2017 semester.

Table 1

UCCCD Course Placement based on ACCUPLACER Mathematics Scores

Test	Score	Course Placement	Testing Options
Arithmetic	20 – 74	MAT 08X Basic arithmetic	
	75 – 120	MAT 09X Introductory Algebra	Take the Elementary Algebra test for placement into MAT 112, 12X, or 14X
Elementary Algebra	20 – 49	MAT 08X Basic Arithmetic	Take the Arithmetic test
	50 – 69	MAT 09X	
	70 – 120	MAT 112, 12X, or 14X	Take the College Level Mathematics test
College Level Mathematics	20 – 31		Take the Elementary Algebra test

Note. The X in the course prefix denotes a different credit value for a specific DM course, where X =1 indicates a 4-credit course and X = 2 indicates a 3-credit course.

One concern was addressing the issue of which mathematics placement test score to use, as students could take one or both of the placement tests multiple times. When I wrote the sampling frame, I assumed that new students took both placement tests, arithmetic and elementary algebra. James (2006) reported that when two mathematics placement tests were used for placement into DM courses, there was a 12.8% higher level of accuracy for predicting success than nonsuccess (79.5% to 66.7%). A review of the sample population used for RQ1 and RQ2 indicated that 49.3% had a score for only the elementary algebra test, while 41% had scores for both the mathematics placement tests. Also, because the cut scores were different for the two placement tests, I had to make a choice between the two mathematics placement scores. Therefore, I decided to only include participants who had a score for the elementary algebra test because 90% of the sample used for RQ1 and RQ2 had a score for the elementary algebra placement test, which meant the same course cut-scores were used for my study. As for multiple attempts at the ACCUPLACER mathematics placement tests, I selected the elementary algebra score that represented the highest score that placed the student into their first DM course. The same criterion was used for the reading comprehension placement test score.

A second concern was that students could have attempted a DM course in six different semesters, either a fall or spring semester. In a similar study, Fitchett, King, and Champion (2011) found no significant difference between fall and spring semester student success rates. For this study, only data from the first DM course was used, which meant that subsequent enrollment in the same course was not used. However, students who took both DM courses would be used for both data sets. Finally, the data collected from all participants were the name of the DM course, the modality of the course (online or face-to-face), the reading comprehension placement score, the mathematics placement score, and the final course grade. Demographic data was also collected: gender, ethnicity, and age, but only for the purpose of describing the targeted population and samples.

Archival Student Data

On October 5, 2017, the associate vice chancellor for academic affairs for UCCCD approved my request for site approval for this dissertation research. I received IRB approval from UCCCD (2017-11-596). Additionally, I received IRB approval from Walden (07-19-18-0572115).

Each campus within UCCCD routinely has a procedure to collect student demographic data during the application process and sends this data to the district where the data is warehoused. Student characteristics are also gathered through surveys during the application process and during the school term, which is also collected and stored at the district according to communications with the office of research. Additionally, UCCCD regularly collects and stores ACCUPLACER placement scores, final student grades, and demographic data for all campuses in the district. Any information that could identify a student was masked by computer-generated identification number, which provided an additional layer of student protection. Data for this study was provided in an Excel spreadsheet. Since the students of UCCCD represent the population and sample source for this study, the office of institutional effectiveness was the appropriate source of data.

Instrumentation and Operationalization of Constructs

The placement instrument for this research was ACCUPLACER, which is a published and validated instrument used to place students into DM courses at UCCCD. ACCUPLACER scores for reading comprehension were used in the study to augment the mathematics placement process. The College Board publishes ACCUPLACER as a commercial placement test (The College Board, 2018c). The reported reliability values for each test are as follows: arithmetic (.93), elementary algebra (.92), and reading comprehension (.89). The College Board indicated that the validity of the ACCUPLACER tests is 70%. The use of this assessment tools was appropriate for this study as UCCCD uses ACCUPLACER.

The results of a study conducted by Mattern and Packman (2009) indicate that ACCUPLACER scores for mathematics are valid at a placement accuracy rate of 59% to

66% for a B or better criterion and a 73% to 84% for C or better criterion. Eskew (2013) confirmed that ACCUPLACER's elementary algebra test correctly placed students with an estimated validity of r = .35 with a 73% prediction for a grade of C. Eskew's study did not include the arithmetic placement test. Similarity, James (2006) reported validity or prediction for success (C or better) at 70.1% for DM courses and a 69.4% for developmental English courses. As stated earlier, this study used the best ACCUPLACER mathematics and reading comprehension placement scores that placed the student into their first DM course.

The Mattern and Packman (2009) study was cited in both the 2015 and 2017 versions of a PowerPoint entitled *ACCUPLACER Reliability and Validity* that was produced by the College Board. This shows that the College Board continues to support the results of this 2009 study, which indicated that ACCUPLACER is both reliable and valid as a predictor of student success. The 2017 presentation did not indicate that changes had been made to the test or recommended cut scores. However, the College Board leaders recommended that educational institutions conduct a validity study on cut scores at least every three years, which UCCC did in 2014 (The College Board, 2018b).

UCCCD indicated that due to a decline in DM student success rates in the Fall 2012 and Spring 2013 semesters, the ACCUPLACER mathematics placement cut scores were revised to be more stringent. These changes increased student success in the fall of 2014. This study used the ACCUPLACER cut scores that became effective for the term beginning spring of 2014. It is for this reason that the dates for collecting student data were between Fall 2014 and Spring 2017 semesters, excluding summer sessions.

Operationalization of variables

This study had one dichotomous independent variable, three continuous independent variables and one dichotomous categorical independent variable. The outcome (dependent) variable for RQ1 and RQ2 was dichotomous and represented either student success or no student success. For RQ1 and RQ2 the independent variables were modality and the composite placement score, which was the summation of the individual placement scores for elementary algebra and reading comprehension. The composite score was continuous with a range of scores from 40 to 240.

Table 2

Operationalization of Variables

Description	Variable	Type	Range of Scores
Dependent	Success	categorial	
Independent	Modality	categorical	
ACCUPLACER Mathematics Placement Tests (Independent)	Arithmetic	continuous	20-120
	Elementary Algebra	continuous	20-120
	College Level Mathematics	continuous	20-120
	Reading Comprehension	continuous	20-120
Constructed (Independent)	Composite	continuous	40-240

Note. Student success were operationalized as successful (yes) for a final grade of A, B, C, or P that allows enrollment in next course in the sequence, while not successful (no) were categorized as a final grade of D, F, W, or Y.

Data Analysis Plan

IBM SPSS software was used for the management and the statistical analysis of the data. While I am using historical data from UCCCD, I was informed by the UCCCD office of research that the data would not be cleaned and may include student records with missing data. Using features of Excel, I removed student records that were missing information (see Chapter 4 for additional information).

The following research questions and hypotheses guided this study:

RQ1: To what extent does a composite placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course basic arithmetic where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, introductory algebra?

H_o1: There is no significant difference in predicting the likelihood of student success with the use of a composite placement score in the online DM course Basic arithmetic.

H_A1: There is a significant difference in predicting the likelihood of student success with the use of a composite placement score in the online developmental

RQ2: To what extent does a composite placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course introductory algebra, where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, introductory algebra?

*H_0*2: There is no significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course introductory algebra.

*H_A*2: There is a significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course introductory algebra.

The details of the analysis plan included the description of the elements of analyzing the data. These elements were hypothesis testing, additional statistical tests, and interpretation of the results. Initially, the sample was described using descriptive statistics, which included participant characteristics, specifically race/ethnicity, gender, and age. Otherwise, binomial logistic regression was used to test the two hypotheses of the research. The following section details the statistical tests and the rationale for the choice of tests used for hypotheses testing.

Laerd Statistics (2015) reported that a logistic regression model has seven assumptions. The first four relate to the design: (a) use of a dichotomous outcome (dependent) variable, (b) at least one predictor (independent) variable that is continuous (c) categories of both the outcome and predictor variables are mutually exclusive and exhaustive, and (d) use of at least 15 to 50 cases per independent variable. These assumptions have been addressed earlier in this chapter. The remaining three assumptions are related to the data and are: (a) a linear relationship between predictor and logit; (b) no multicollinearity among the predictor variables; and (c) no influential data points, such as high leverage points, or significant outliers. A discussion of these assumptions follows.

The assumption that a linear relationship exists between the continuous predictor variable and logit (log odds) was tested using the Box-Tidwell procedure, which assessed if the continuous predictor and the logit (log odds) had a linear relationship. A significant interaction would indicate a non-linear relationship. Additional testing using Bonferroni correction was not required to determine that the relationship between the continuous variable (composite placement score) and the logit.

The remaining two assumptions were concerned about multicollinearity and outliers. While logistic regression does not assume a normal distribution on the outcome variable, it does assume independent observations and no multicollinearity between two predictor variables (Osborne, 2015; Weiss & Dardick, 2016). The analysis included looking at the correlation coefficients and tolerance/VIF values to test for can multicollinearity. I ensured the accuracy of the findings by first addressing the assumption associated with binary logistic regression.

Each of the null and alternative hypotheses focused on the presence of statistical and significant composite placement score for a specific online UCCCD DM course. Binary logistic regression results were used to build the models for predicting the likelihood of student success. That is, I used logistic regression testing to examine the relationship between student success in a specific online DM (Basic Arithmetic MAT08X and/or Introductory Algebra MAT09X) course and a composite ACCUPLACER placement score.

If p represents the probability of success in an online DM course, then the logistic model was as follows:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k$$

where $X_1, \ldots, X_k$ are the predictor variable's values for each of the ACCUPLACER scores.

SPSS generated a table that includes the β coefficients of the model. The β coefficient indicates the change in the log odds with a one-unit change in the independent variable, as other predictor variables are held constant (Osborne, 2015). The null hypothesis was tested using the Wald's χ^2 ratio statistic. The Wald's χ^2 ratio indicated a statistical significance for the predictor variables and any interaction variables (see Osborne, 2015).

Goodness-of-fit was measured by the Hosmer-Lemeshow X^2 test, the log-likelihood (LL) function, and the deviance (-2LL) value. Other tests of goodness of fit include Cox and Snell's R^2 and Nagelkerke's R^2, with the latter being the preferred as its scores have 1 as a maximum value (Laerd Statistics, 2015; Weiss & Dardick, 2016). To ensure that the models were a good fit, all or some measures were used to determine the goodness-of-fit for the models.

Along with the goodness-of-fit measures, strength or explained variance in the dependent variable was assessed with the Cox & Snell R^2 and /or Nagelkerke R^2 tests. SPSS also generated a table, Omnibus Tests of Model Coefficients, which indicated the statistical significance of a model ($p < .001$). Hence, this table indicated how well a model predicts categories of the outcome variable when compared with a model with no predictor variables. This table also showed a chi-square value. These results were used to answer the research questions.

The effect of predictor variables (modality and composite placement score) were explained using odds ratios (labeled EXP (β)) at the significant level of .05 (Wolfle & Williams, 2014). The odds ratio (*OR*) indicated the extent that each predictor variable contributes to the outcome variables of student success and modality. An *OR* of 1 signifies no relationship, a value greater than 1 signifies a positive relationship, and a value less than 1 signifies a negative relationship (Osborne, 2015). Davidson and Petrosko (2014) recommended converting negative odds ratios to inverse odds ratios to clarify the interpretation. The *OR* is adjusted to account for the effects of other predictors in the model (Osborne, 2015). The results of my research were reported as odds ratios and percentages of likelihood of success, because the use of a logit or log odds is difficult for most readers to understand and interpret.

Threats to Validity

As a pre-experimental research design, I needed to address valid concerns. A threat to a studies external validity included the failure to address potential interactions between variables and the lack of specificity of variables. As there were two predictors in the predictive model, modality and composite score (combined placement scores), hypothesis testing involved the inclusion of both predictors into the models, which allowed for the controlling of predictors during the assessment of each predictor variable (Osborne, 2015). Rutkowski and Delandshere (2016) wrote that three fundamental threats to validity (external, internal, or statistical conclusion) work in unison to strengthen or weaken a study. However, it was reported that threats to validity occur in experimental studies when the researcher draws inferences from cause-effect or causal relationships (Rutkowski & Delandshere, 2016). The literature search did not identify any potential confounding variables appropriate for this research that could offer another explanation for the results and findings. For this research, the use of logistic regression and a large sample size should have improved the generalizability of the study, which signifies that the research design had the potential to mitigate or at least minimize any threats to external validity. However, because of the poor quality of data provided by UCCCD, I was not able to use the entire targeted population, which resulted in the need to use two sample populations, one for each RQ, with smaller sizes than originally anticipated. The smaller sample sizes should not influence the generalizability of this study as the sample represented three years of data that offered a longitudinal view of the data, which made the results generalizable.

External Validity

A threat to a studies external validity included the lack of not addressing potential interactions between variables and the lack of specificity of variables. As there are two predictors in each model, hypothesis testing involved the inclusion of all predictors and interactions into the models, which allowed for the controlling of predictors during the assessment of each predictor variable (Osborne, 2015). Tabachnick and Fidell (2013) warned researchers that a large sample size could indicate a significant interaction but should not concern the researcher.

Osborne (2015) explained that in a logistic regression model "external validation refers to validating the equation on a population that may have substantial differences than the development sample" and has "limited usefulness" (p. 339). It was also noted that the use of a dichotomous outcome and large sample size would minimize threats to external validity (Osborne, 2015). With respect to my study, the use of logistic regression and a large sample size improved the generalizability of the study, which meant the design had the potential to mitigate or at least minimize any threats to external validity.

Internal Validity

Campbell and Stanley (1963) explained that with a pre-experimental research design the two groups, 0_1 and 0_2, could be different before the treatment X. This indicated that for my study the online and the face-to-face groups could differ prior to students' decision on the modality for their DM course. I had no control beyond sorting sample participants by their DM course, placement scores, and choice of modality.

Other threats to interval validity focused on the attrition of participants. Experimental mortality (e.g. where participants drop out of the experiment) was suggested as a potential confounded variable and a potential threat to validity for a pre-experimental research design (see Campbell & Stanley, 1963). For my study, students who withdrew prior to the seventh week of the semester represented experimental mortality. UCCCD withdrawal policy indicated that students who withdrew after the seventh week received either a W or Y. Those students who withdrew after the seventh week were included in the sample and recorded as not being successful.

Statistical Conclusion Validity

Creswell (2009) explained that threats to statistical conclusion validity arose when a design violated statistical assumptions. Laerd Statistics (2015) reported that a logistic regression design has seven assumptions. The first four are related to the design: (a) use of a dichotomous outcome (dependent) variable, (b) at least one predictor (independent) variable that is continuous or nominal, (c) categories of both the outcome and predictor variables are mutually exclusive and exhaustive, and (d) use of at least 15 to 50 cases per independent variable. The remaining three are related to the data and are: (a) a linear relationship between predictor and logit; (b) no multicollinearity among the predictor variables; and (c) no influential data points, such as high leverage points, or significant outliers. SPSS was used to test these three data assumptions. As described earlier in this chapter, all assumptions were addressed.

Ethical Procedures

On October 5, 2017, the UCCCD Associate Vice Chancellor for Academic Affairs approved my request for site approval for this dissertation study. I received IRB approval from UCCCD (2017-11-596) and Walden (07-19-18-0572115). Once Walden IRB approval was gained, the director of the UCCCD's Office of Institutional Effectiveness provided the archival student data for this research.

Each campus within UCCCD routinely collected student demographic data during the application process, which is then warehoused at UCCCD's office of research. Student characteristics were gathered through surveys during the application process and during the school term, which were also collected and stored at the district according to communications with the Office of Institutional Effectiveness. The data I received represented historical data collected between Fall of 2014 and Spring of 2017. Additionally, UCCCD's Office of Institutional Effectiveness collects and stores ACCUPLACER placement scores and final student grades. For my study, UCCCD's Office of Institutional Effectiveness indicated that all student data were made anonymous by a computer-generated identification number for each student, which acted as an additional layer of student protection. The student data was provided in an Excel spreadsheet. All data associated with this study will be stored on thumb drives and will be secured for a minimum of five years. Any request by other researchers for access to the UCCCD student data used for this research will be denied thus ensuring the protection of confidential data.

Summary

Within Chapter 3, I provided details about the research design and methodology of the method of inquiry for my study. My study used a static-group comparison research design and logistic regression analysis to create two models that predicted the likelihood of student success in online DM. The static-group comparison research design, as a pre-experimental quantitative research design, was thoroughly explained in this chapter. Laerd Statistics (2015) stated that addressing the assumptions associated with a binomial logistic regression supports the notion of the accuracy and the goodness of fit of the predictive models. This chapter also provided details on how all assumptions and concerns about validity were addressed to ensure the models accurately predict the likelihood of student success. An example of how the study addressed validity and reliability was to show that the UCCCD's use of ACCUPLACER was appropriate since the reported reliability values for each test are as follows: arithmetic (.93), elementary algebra (.92), and reading comprehension (.89). In addition, the College Board (2018b) indicated that the validity of the ACCUPLACER tests is 70%.

Chapter 4 begins with a description of the data collection process that included descriptive statistics on participating UCCCD students. Also included in the following chapter are results of the SPSS statistical tests conducted. Results, based on the creation of a predictive models using logistic regression, are explained and summarized in a series of tables. Chapter 4 includes a summary of the how the results answer the research questions and of additional statistical tests that were conduct

Chapter 4: Results

The purpose of this pre-experimental quantitative study was to examine if a change in UCCCD's policy and practices for student placement into DM courses could improve predicting student success in online DM courses. This research examined if a composite placement assessment score was a significant and statistical predictor of student success in the online DM courses of basic arithmetic and/or introductory algebra, which are taught at the colleges associated with UCCCD.

The following research questions and hypotheses guided this study:

RQ1: To what extent does a composite placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course basic arithmetic where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, introductory algebra?

$H_0$1: There is no significant difference in predicting the likelihood of student success with the use of a composite placement score in the online DM course basic arithmetic.

H_A1: There is a significant difference in predicting the likelihood of student success with the use of a composite placement score in the online DM course basic arithmetic.

RQ2: To what extent does a composite placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course introductory algebra, where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, introductory algebra?

$H_0$2: There is no significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course introductory algebra.

H_A2: There is a significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course introductory algebra.

In this chapter, I will present the results of determining the likelihood of student success in online DM courses when a composite placement score (combination of both reading comprehension and mathematics placement scores) was used as a predictive factor. In the first section of this chapter, I briefly reviewed the purpose, research questions, and hypotheses. Subsequent sections described the data collection method, treatment, and results. In the final section, the results of the statistical analysis, which includes tables, are organized by the research questions.

Data Collection

Data for this study was collected by UCCCD campus advisors between August 2014 and May 2017 and then stored at the UCCCD Office of Institutional Effectiveness. The original number of participants was 40,301. However, after data screening and cleaning, there were 39,585 participants. Unfortunately, the data file's organization did not lend itself to using all the participants as had been anticipated and noted in Chapter 3. I concluded that a stratified sampling method would best fit my study because this sampling method divided the targeted population into smaller groups (strata) based on shared characteristics. This type of sampling ensures that each stratum is proportional in size to the targeted population, the sample is highly representative of the population under study, and the statistical findings are valid (see Laerd Dissertation, 2012).

I determined the first stratum was the course type (basic arithmetic or introductory algebra), and the second stratum was modality (online or face-to-face). Based on G*Power and Survey Monkey's sample calculators, I determined that this study required a sample size of at least 767. Table 3 below shows the baseline descriptive and demographic characteristics of the sample. Table 3 also displays the comparison between the targeted population as described in Chapter 3 and the stratified sample described above.

The student characteristics between the targeted population and the sample closely aligned. For the most part, all four gender characteristics were similar as were the age ranges. Both the targeted population and sample had more females than male, and the 18 to 25 age range represented the largest group. UCCCD collects data on eight different ethnicities or races. Of these, Hispanics and Whites comprised most of the students. Due to the protocols of stratified sampling, the target population and sample are proportional, which includes gender characteristics that individually represented less than 4% of the target population.

Enrollment characteristics of the targeted population and the sample population are compared Table 3. The enrollment rates between the targeted population and the sample population differed by 9% for enrollment in basic arithmetic, and by 8.2% for enrollment in introductory algebra. This difference was attributed to the targeted population students having at least one ACCUPLACER math score, while the sample population excluded students who did not have a score for the elementary algebra test.

Table 3

Demographic and Institutional Characteristics

Characteristic	Targeted Population (*N = 39,585)* Frequency (n)	%	Sample (*N = 767)* Frequency (n)	%
Gender				
Female	21586	54.5	392	51.1
Male	17368	43.9	359	46.8
Transgender	123	.3	3	.4
Unspecified	508	1.3	13	1.7
Age				
18-25	29772	75.2	586	76.4
26-35	6372	16.2	119	15.5
36-45	2229	5.7	38	5.0
46-55	933	2.4	17	2.2
Over 55	279	.5	7	.9
Ethnicity/Race				
American Indian	1398	3.5	24	3.1
Asian	945	2.4	21	2.7
Black	4093	10.3	89	11.6
Hawaiian	149	.4	4	.5
Hispanic	15571	39.3	289	37.7
Not Specified	2613	6.6	45	5.9
Two/More	1058	2.7	20	2.6
White	13758	34.8	275	35.9
Enrollment				
Basic Arithmetic	16658	42.1	386	50.3
Intro. Algebra	22927	57.9	381	49.7
Face-to-Face	33750	85.3	651	84.9
Online	5835	14.7	116	15.1

After a further review of the data, I concluded that the ACCUPLACER elementary algebra test score and not the arithmetic test score would be used for the composite score. Only 4% (34 students) of the stratified sample did not have an elementary algebra test score. Students without a score for the elementary algebra test were replaced with students who had scores for one or both of the math placements tests. I used the original random list and chose the next 34 students who met this criterion. Table 4 shows descriptive statistics for the ACCUPLACER placement scores and the constructed predictor variable (composite score) for the final sample. This table shows that on average students taking the elementary algebra placement test had a mean score of about 46, which places them into the basic arithmetic course. Students taking the reading comprehension placement test had a mean score of 75.99, which is three points above the cut score for DE reading course, and indicates that on average students in the sample population had minimal reading comprehension proficiency. The mean for the composite score was 109.67. The scores for the composite score can range from 40 to 240. In other words, a student with a composite score of 109 could place into basic arithmetic and place into the highest developmental reading course or the lowest college-credit reading course. A composite score of 109 could also indicate placement into introductory algebra, but requires the student to enroll in a developmental reading course. Finally, a student with a composite score of 109 could enroll in intermediate algebra, a college-level course, but would require enrollment into one of the two lowest levels of developmental reading.

Table 4

ACCUPLACER Placement Scores for the Sample (N=767)

Placement Test	Minimum	Maximum	Mean	*SD*
Elementary Algebra	20	103	46.18	16.18
Reading Comprehension	21	118	75.99	19.93
Composite Score	42	188	109.67	25.503

UCCCD placement policy indicated that the ACCUPLACER range for placing into basic arithmetic was 20 to 49, 50 to 69 for introductory algebra, and 70 to 120 for a college level course (e.g., college mathematics or college algebra). The sample population (n = 386) for RQ1 (basic arithmetic) had mathematics placement scores ranging from 20 to 94. Eight percent (31 students) of the sample for basic arithmetic had placement scores outside the range (scores greater than 49) for enrollment into basic arithmetic. The sample population (n = 381) for RQ2 (introductory algebra) had placement scores ranging from 21 to 103. The sample for introductory algebra had 116 students (30.4%) who had placement scores outside the recommended range for placement into introductory algebra (50 to 69). This signifies that there were students in both courses that qualified to be in a different level of DM course or a college-level mathematics course (see Table 5). The characteristics of the sample population were proportionate to the targeted population (see Table 3). I do not have data on the percentage of students in the targeted population (39,585) who chose a DM course or college-level mathematics course different from the course suggested by ACCUPLACER results. However, since my sample populations are the result of stratified sampling, I would predict the results would be comparable. The number of students whose choice a mathematics course not suggested by the ACCUPLACER placement score are characterized in this study as being *misplaced students by choice*. I think that these misplaced students by choice could have influenced the analysis results and findings for RQ2. More details regarding misplaced students by choice can be found in Chapter 5.

Table 5

Success Rate of Misplaced Students by Course Enrollment

	Score Range 20 to 49 Basic Arithmetic			Score Range 50 to 64 Into to Algebra			Score Range 70 to 120 Intermediate Algebra/College Arithmetic		
Course Enrolled	Count	Pass (%)	Failed (%)	Count	Pass (%)	Failed (%)	Count	Pass (%)	Failed (%)
Basic Arithmetic (*n* = 31)	NA	NA	NA	21	15 (71%)	6 (29%)	10	8 (80%)	2 (20%)
Introductory Algebra (*n* = 116)	89	57 (64%)	32 (36%)	NA	NA	NA	27	16 (59%)	11 (41%)

Note: Pass or fail percent based on the number of misplaced students in each class. NA means students chose the course suggested by ACCUPLACER testing, hence not misplaced.

Treatment

The treatment for this study was enrollment into online basic arithmetic or introductory algebra. The control group for this study were students who enrolled into the face-to-face version of basic arithmetic or introductory algebra. For this study, student success was used to measure the difference between the two groups. The observed difference between the two groups was assumed to be the result of the treatment and the composite placement score. While there was not a pre-/posttest for this study, mathematics placement scores were used by the students to determine enrollment into a DM course. This study identified that 30% of the students who enrolled into introductory algebra were misplaced by choice. As previously discussed, misplacement by choice signifies that student’s chose a DM course that was not indicated by their mathematics placement score. As a result, a misplaced by choice student may have chosen the online version of introductory algebra due to their stronger performance on the mathematics placement, which could influence the results of this study. As UCCCD does not have a placement policy on modality, students self-select the modality of their DM course based on personal reasons.

Results of the Statistical Analysis

Assumptions associated with a logistic regression were tested prior to beginning the analysis. Unlike other regressions, logistic regression does not assume that the predictor and outcome variables have a linear relationship (see Laerd Statistics, 2015). In addition, Laerd Statistics (2015) indicated that logistic regression does not assume homoscedasticity (data values are spread out to the same extent for each group in the study) or normality (data values have normal or bell curve distribution). For each research question the three assumptions of logistic regression were tested and were met: (a) linearity between the continuous independent variable (composite placement score) and the dichotomous dependent variable (student success), (b) identification of the presence of outliers, and (c) indication of collinearity between the constructed placement variable and modality (Laerd Statistics, 2015). A discussion of each of the assumptions follows.

Assumption 1: Linearity

This assumption indicates the need for a linear relationship between the continuous predictor variable (composite placement score) and the logit transformation of the dependent variable (student success). A Box-Tidwell procedure indicated that a linear relationship existed between the predictive composite score variable and the outcome variable of student success, because the interaction term (ln composite score by composite score) was not statistically significant ($p > .431$). Therefore, the first assumption was met.

Assumption 2: Identification of Outliers

Outliers were identified using residuals (the difference between an observed value of the dependent variable and the predicted value). For RQ1, after studentizing the values (mathematically determining if a residual value had an absolute value larger than 3), SPSS indicated the presence of one outlier. This single outlier was kept in the analysis because the absolute value of the outlier was equal to 3.2. Statistically this single student's residual was not great enough to influence the results. For RQ2, no outliers were identified.

Assumption 3: No Collinearity

Collinearity (correlation between predictor variables) was tested using SPSS by running a linear regression on the independent (predictor) variables of modality and the composite score. Collinearity indicates the relationship between the regression coefficients found in the model. The predictor variables should not be correlated and are tested through examining values for variance inflation factor (VIF), and *tolerance*. VIF is the reciprocal of tolerance and tolerance is the measure of collinearity (Field, 2011; Laerd Statistics, 2015). Field (2011) reported that a VIF value of 1 indicates no correlation, a value between 1 and 5 indicates a moderate correlation, and a value greater than 5 indicates a high level of correlation. The results of this study indicated that for RQ1, the VIF = 1.38 and for RQ2, the VIF = 2.98.

Statistical Analysis Findings

The logistic regression model (equation) for each of the research questions predicts the probability of a student being successful in a DM course using the student's composite score and choice of modality. The results of this study's logistic regression results were used to classify (predict) students' probability of success. Before using a model to predict student success, I thought it was important to first compare observed student success among the targeted population (N = 39,585), the stratified sample (n = 767), sample population for RQ1 (n = 386), and the sample population for RQ2 (n = 381).

Table 6 shows the observed success count and percentage, regardless of the DM course, for each modality (face-to-face or online) for the targeted population (N= 39,585). Sixty-four percent of UCCCD students in the targeted population were successful in the face-to-face DM courses, while online students were evenly split between success and no success. The targeted population had a student success rate of 62% in the DM courses basic arithmetic and introductory algebra regardless of modality.

Table 6

Targeted Population: Student Success and Modality (N = 39,585)

		Student Success		Total
		No	Yes	
Modality	Face-to-Face	12,216 36.2%	21,534 63.8%	33,750 100.0%
	Online	2,933 50.3%	2,902 49.7%	5,835 100.0%
Total		15,149 38.3%	24,436 61.7%	39,585 100.0%

Table 7 shows the observed modality success rates for the sample population as a group, while Table 8 shows the modality student success rates for basic arithmetic and introductory algebra. In general, the percentage of successful students in face-to-face was similar for the target population, sample, and course participants: about 35% failed and 65% passed. In contrast, the percentage of students who were successful in online courses varied among the three different sample groups. In the targeted population (n = 39,585) generally about 50% of the students either passed or failed, while in the sample (n = 767) about 40% failed and about 60% passed. In basic arithmetic (n = 386), 35% failed and 65% passed; while in the introductory algebra (381), 46% failed and 54% passed. The results for the basic arithmetic course were similar to the results of Fong et al. (2015), who reported a 64% success rate in arithmetic at the post-secondary level. The results for the introductory algebra course were six percent lower when compared to the success rate of 70% that was reported by Fong et al. (2015). However, the introductory algebra sample population's results could have been skewed due to the number of misplaced students.

Table 7

Sample: Student Success and Modality (n = 767)

		Student Success		Total
		No	Yes	
Modality	Face-to-Face	215 33.0%	436 67.0%	651 100.0%
	Online	46 39.7%	70 60.3%	116 100.0%
Total		261 34.0%	506 66.0%	767 100.0%

Table 8 shows the results of a 2 x 2 cross-tabulation organized by modality and student success for the sample participants in each course, basic arithmetic (08X) and introductory algebra (09X). Using these results, I not only calculated the unconditional odds (i.e. the odds in the sample as a whole) for each course and the conditional odds (i.e. conditional on course modality), but also the probabilities of student success. The unconditional odds of the likelihood of success for any student in a basic arithmetic are 251/135 = 1.86, which means that a randomly chosen student from the basic arithmetic sample are 1.86 times more likely to be successful than not successful. The unconditional odds of the likelihood of success for any student in introductory algebra course are 255/126 = 2.02, which means that a randomly chosen student from this course's sample are 2.02 times more likely to be successful than not successful. The probability of success in a basic arithmetic course is 251/386 = .650 (i.e. an 65.0% chance that a student will be successful in basic arithmetic), while in an introductory algebra course the probability of success is 255/381 = .669 or 66.9% chance of success.

Therefore, the data indicates that there is little difference in the chance of success in either DM course.

In contrast, the results are different when online success is compared to face-to-face success. Sixty percent of students who took an online DM course at UCCCD were successful, which is higher than Jaggars et al. (2013) reported study findings of 38%. While, Jaggars et al. (2013) reported a 57% success rate for face-to-face DM courses, 67.5% of the UCCCD students in a face-to-face DM course were successful. The data indicates that the success rates for UCCCD students in DM courses are higher when compared to previous research cited above.

The conditional odds of a randomly chosen student in an online basic arithmetic student being successful are .656/(1-.656) = 1.907. The conditional odds of a randomly chosen student in an online introductory algebra course are .538/(1-.538) = 1.165, which is considerably less than the odds of success in an online basic arithmetic course. These conditional odds were used to calculate the odds ratio. For basic arithmetic, the odds ratio is 1.907/1.849 = 1.0313, which indicates that online students and face-to-face students have almost the same likelihood of success. For introductory algebra, the odds ratio of 1.165/2.226 = .523, which means that students in an online introductory algebra course are less likely to be success than students in the face-to-face introductory algebra course. To increase the usability of the findings from a 2 x 2 cross tabulation, the results were presented using odds, odds ratios and associated probabilities, as suggested by Peng, Lee, and Ingersoll (2002) and noted in Chapter 3. In addition, these results are similar to the results found using SPSSs logistic regression testing.

Table 8

Student Success by Course (n_{08X} = 386; n_{09X}=381)

		Basic Arithmetic (08X) Student Success		Total	Intro. Alg (09X) Student Success		Total
		No	Yes		No	Yes	
Modality	Face-to-Face	113	209	322	102	227	329
		35.1%	64.9%	100.0%	31.0%	69.0%	100.0%
	Online	22	42	64	24	28	52
		34.4%	65.6%	100.0%	46.2%	53.8%	100.0%
Total		135	251	386	126	255	381
		35.0%	65.0%	100.0%	33.1%	66.9%	100%

The following two sections report on the logistic regression statistical analysis findings for each of the two research questions and hypotheses. Each section includes evaluations on the predictive model, individual predictors, goodness-of-fit, and predicted probabilities. Confidence intervals are included for the odds ratio (Exp(β)). Categorical (dummy) coding for the variables was as follows: success (no = 0, yes = 1) and modality (face-to-face = 0, online = 1). The decision to reject or not reject the null hypotheses was based on the multiple measures: Hosmer and Lemeshow goodness of fit test, Omnibus Tests of Model Coefficients, -2 Log Likelihood, Cox & Snell R^2, and Nagelkerke R^2.

Research Question 1: Basic Arithmetic. The first research question asked: To what extent does a composite placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course basic arithmetic where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, introductory algebra? The research design supported examining the extent of predicting whether modality (as a treatment) and a composite score influenced student success in an online DM course (the treatment group) when compared to the same course offered as a face-to-face modality (the control group).

To answer the first research question and test the null hypothesis, a predictive model consisting of two variables was developed based on an SPSS analysis of the data associated with the sample for basic arithmetic. This model (an equation) examined the relationship between (a) student success in the DM course basic arithmetic successful and (b) the students' composite placement score and choice of course modality. The model originally included an interactive variable (composite score by modality) but this variable was not included in the final model (equation) as it was not a statistically significant contributor (p = .545) to the model's ability to predict student success. The following hypothetical predictive model (equation) was developed using the results, shown in Table 9, of the logistic regression.

*Predicted logit (student success) = -1.902 + (.024) *composite score + (-.154) *modality*

The evaluation of the logistic regression model began with evaluating the results of the statistical tests for each of the predictor variables (See Table 9).

Table 9

Variables in the Equation for Research Question 1

	B	SE β	Wald's χ^2	*df*	Sig. *(p)*	Exp(β) Odds Ratio	95 % C.I. for Exp(β) Lower	Upper
Constant	-1.902	.502	14.328	1	.000	.149		
Composite Score	.024	.005	25.751	1	.000	1.024	1.015	1.033
Modality	-.154	.299	.266	1	.606	.857	.477	1.539

According to the predictive model for student success, success was positively related to the composite placement score (β = .024, Exp(β) = 1.024, p < .001) and the composite placement score added statistically and significantly to the model. The coefficient (β) for the composite placement score indicate the change in the log odds (logit) for success that occurs for a one-unit change for each of the predictive variables (composite score). The log odds change for the composite placement score is .024, which indicates an increase of the log odds for each increase in the composite score. A more intuitive way to understand the results is to interpret the odds ratios (OR). The OR for the composite placement score (Exp(β) = 1.024), indicates that the odds of student success in a basic arithmetic is 1.024 times greater for every one-point increase in the composite placement score. In other words, improvement in the composite placement score results in an increase in the odds of a student being successful in a basic arithmetic course at UCCCD.

Modality was not statistically significant in the model for RQ1 (p > .05). I kept modality in the model equation because modality was a predictor variable in the research design, the research question, and in the null hypothesis for basic arithmetic. The coefficient (β) for modality indicated a decrease in the log odds for student success for online basic arithmetic students. The OR for modality, as a predictor of the likelihood of student success, (β = -.154, Exp(β) = .857, p = .606), indicated that a student's odds of success decreased by a factor of 0.857 for online students than for face-to-face students in basic arithmetic. Put another way, face-to-face students' odds of success are 1.17 (inverse of .857) times higher than for online students.

My decision to include a predictive variable that was not significant was also based on the work of other researchers. Peng et al. (2002) argued that the lack of significance does not indicate the removal of these variables in the model if the model is a good fit to the data. A *p*-value greater than .05 is considered borderline significant due to the *p*-value being less than .10, but in hypothesis testing a *p*-value less than .10 should not be accepted for this single reason, regardless if the researcher set the significant value at $p < .05$ (Neath, 2016; Wasserstein & Lazar, 2016). The coefficients of the model also contributed to the final decision as to whether or not the null hypothesis should be rejected.

I used multiple measures to determine the statistical significance of the model and whether the model for predicting student success in basic arithmetic fit the data provided by UCCCD. This evaluation of model fit was key to using the model for RQ1 because modality had a statistical significance greater than 0.05. Statistical significance for this study was based on an alpha level of 0.05. The results of the omnibus tests of model coefficients, as shown in Table 10, indicated that the model was statistically significant, χ^2 (2) = 28.485, $p < .0005$. These results indicated that the model was able to predict student success with the inclusion of the predictor variables of composite score and modality. The omnibus tests results were also used in determining whether the null hypothesis should be rejected.

Table 10

Omnibus Tests of Model Coefficients for Research Question 1

	Chi-square (χ^2)	df	Sig. (p)
Step	28.485	2	.000 (reported as $p < .0005$)
Block	28.485	2	.000 (reported as $p < .0005$)
Model	28.485	2	.000 (reported as $p < .0005$)

A different method of determining if the model was a good fit is to analyze how poorly the model predicted student success. The Hosmer and Lemeshow goodness-of-fit test results, as shown in Table 11, indicated that the model was a good fit because the *p*-value was not significant ($p = .271$). For this test, the results indicate a goodness-of-fit when the results are not statistically significant. The results of the Hosmer and Lemeshow test are also used in determining whether the null hypothesis should be rejected.

Table 11

Hosmer and Lemeshow Test (*HL*χ^2) *for Research Question 1*

Step	Chi-square (χ^2)	df	Sig. (p)
Step 1	9.909	8	.271

The Nagelkerke R^2 test (see Table 12) can be used for measuring a model's effect size and the amount of variation in the dependent variable (student success). The Nagelkerke $R^2 = .098$ indicated that about 10% of the variation in student success was explained by the model. The Nagelkerke R^2 test values range from zero to one where the value of one means that the model accounts for 100% of the variance in the outcome. Therefore, the model summary indicated that with the addition of both predictor variables (composite placement score and modality) to the model about 10% of the variation in student success was explained. Even though the result of the effect size was small, it did indicate an improvement (i.e., a difference between a model with no variables and a model with two variables) in the model's ability to predict the likelihood of student success.

Table 12

Model Summary for Research Question 1

	-2 Log Likelihood (-2LL)	Cox & Snell R^2	Nagelkerke R^2
Step 1	471.220	.071	.098

A classification table was used to estimate the probability of student success by assessing the effectiveness of the model's ability to correctly classify student success or student failure. The frequency to which the logistic regression model predicted probabilities of success and no success (failure) compared to the actual frequency of success and no success (failure) is shown in Table 13. The classification table shows that the model with no predictors correctly classified 65.0% of the students as being success who were in fact successful in basic arithmetic. After modality and the composite score were added to the model, the model improved its predictive ability to 65.8%. The addition of the two predictor variables slightly improved (0.8%) the predictive ability of the model. This result was similar to the Nagelkerke R Square results in that both results indicate a weak model for predicting the likelihood of student success in basic arithmetic.

The information found in the classification table (see Table 13) was also used to calculate sensitivity and specificity, which are measures also used in null hypothesis testing. Sensitivity is the ability of the model to correctly predict success for those students who were observed to be successful in the data. The model for basic arithmetic predicted success correctly 88.4% of the time. Similarly, specificity measures the ability of the model to correctly predict non-successful students who were observed not being successful. The specificity of this model was 23.7%, which indicates that the model was only able to correctly predicted student failure 23.7% of the time.

Table 13

Classification Table

			Predicted		
			Success		Percentage
	Observed		No	`Yes	Correct
Step 0	Success	No	0	135	.0
		Yes	0	251	100.0
Overall Percentage					65.0
Step 1	Success	No	32	103	23.7
		Yes	29	222	88.4
Overall Percentage					65.8

Note. The cut score is .500. At Step 0 no variables are in the model. At Step 1 both predictor variables are included in the model.

In summary, a binomial logistic regression was performed to determine the effects of modality and a composite placement score on predicting the likelihood that students in a UCCCD online basic arithmetic course would be successful. The model was statistically significant, χ^2 (2) = 28.485, $p < .0005$. The model explained 9.8% (Nagelkerke R^2) of the variance in student success and improved predicting the likelihood of student success in the basic arithmetic course. As a predictor, the composite score was statistically significant ($p < .001$), while modality was not statistically significant (p = .606). The inclusion of modality as a nonsignificant variable did not influence the results of multiple goodness-of-fit tests that indicated the model was a good fit for the data. Modality as a predictor was kept in the model, even though not significant, because the research design, research question, and null hypothesis required inclusion of the composite score. As a reminder, the null hypothesis for RQ1 is "There is no significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course basic arithmetic." The results indicated that the model was able to predict, with a significant difference, the likelihood of student success with the use of a statistically and significant composite placement score. Therefore, I determined that the null hypothesis for RQ1 should be rejected and the alternative hypothesis should not be rejected.

Research Question 2: Introductory Algebra

The second research question asked: To what extent does a composite placement score, based on the ACCUPLACER scores for reading comprehension and mathematics, statistically and significantly predict the likelihood of student success in the online DM course introductory algebra where success is measured by a final grade (A, B, C, or P) that makes the student eligible for the next mathematics course, intermediate algebra? The research design supported examining the extent of predicting whether modality (as a treatment) and a composite score influenced student success in an online DM course (the treatment group) when compared to the same course offered as a face-to-face modality (the control group).

To answer the second research question and test the null hypothesis, a model consisting of two-predictor variables was developed based on sample data. The sample (*n*

= 381) represented students taking introductory algebra as their first UCCCD mathematics course. I used a predictive model to examine the relationship between (a) the likelihood that a student in the DM course introductory algebra is successful (dependent variable) and (b) the student's composite placement score and choice of course modality (independent variables). The model originally included an interactive variable (composite score by modality) but this variable was not included in the final model (equation) as it did not significantly (p = .140) contribute to the model's ability to predict student success. The following hypothetical predictive model (equation) was developed using the results, shown in Table 14, of the logistic regression.

*Predicted logit (student success) = -.274 + (.008) *composite score + (-.648) *modality*

The evaluation of the logistic regression model began with evaluating the results of the statistical tests for each of the predictor variables (see Table 14).

Table 14

Variables in the Equation for Research Question 2

	β	SE β	Wald's χ^2	*df*	Sig. *(p)*	Exp(β) Odds Ratio	95 % C.I. for Exp(β) Lower	Upper
Constant	-.274	.616	.197	1	.657	.760		
Composite Score	.008	.005	3.113	1	.078	1.008	.999	1.017
Modality	-.648	.304	4.553	1	.033	.523	.289	.949

Note. Modality is for online compared to face-to-face.

According to this predictive model for student success in introductory algebra, modality was statistically significant (p = .033) and negatively related to student success ($\beta = -.648$, $p < .05$). This means that the students in online introductory algebra are less likely to be successful when compared to students in the face-to-face environment. The results indicated that modality added significantly and statistically to the model, while the composite score ($p > .078$) was not statistically significant and did not significantly contribute to the model. As previously noted, the lack of significance does not indicate the removal of these variables in the model if the model is a good fit to the data. The composite score was kept in the model, even though not significant, because the research question, null hypothesis, and research design required inclusion of the composite score.

Odd ratios (Exp(β)), calculated from the exponentiated coefficients (β), indicates the change in the odds of student success decreased when modality changed from face-to-face to online. The OR for modality (β = -.0648, $Exp(\beta)$ = .523, $p < .05$) indicated that the odds of success for students in the online course decreased by a factor of 0.523. Put another way, face-to-face students' odds of success are 1.912 (inverse of 0.523) times higher than for online students.

Next, I evaluated the logistic regression model to determine whether the model for predicting student success in an introductory algebra course fit the data provided by UCCCD. Similar to RQ1, this evaluation is key as I am using the model for RQ2 and the statistical significance for the composite score was greater than 0.05. The results of the omnibus tests of model coefficients, as shown in Table 15, indicated that the model was statistically significant, χ^2 (2) = 7.590, $p < .022$. However, the ability of the model for introductory algebra to predict the likelihood of success is not as strong as the model for basic arithmetic.

Table 15

Omnibus Tests of Model Coefficients for Research Question 2

	Chi-square (χ^2)	df	Sig. (p)
Step	7.590	2	.022
Block	7.590	2	.022
Model	7.590	2	.022

I used the Hosmer and Lemeshow goodness-of-fit test to measure whether the model was a good fit for the data. The test results, as shown in Table 16, indicated that the model was a good fit because the p-value was not significant (p = .223). Similar to RQ1, the results of the Hosmer and Lemeshow test were also used for null hypothesis testing.

Table 16

Hosmer and Lemeshow Test (*HL*χ^2) *for Research Question 2*

Step	Chi-square (χ^2)	df	Sig. (p)
Step 1	10.632	8	.223

The Nagelkerke R^2 test (see Table 17) was used for measuring the model's goodness-of-fit. The Nagelkerke R^2 = .027, which indicated that 2.7% of variation was explained when the two predictors, composite score and modality, were added to the model. Even though the results of the Nagelkerke R^2 was small, the results showed that the model fit the data.

Table 17

Model Summary for Research Question 2

	-2 Log Likelihood (-2LL)	Cox & Snell R^2	Nagelkerke R^2
Step 1	476.035	.020	.027

Similar to RQ1, I used logistic regression to estimate the probability of student success using a classification table (see Table 18). The classification table indicated that with only the constant in the model, the model correctly classified 66.9% of the students as being success who were actually successful in introductory algebra. However, when modality and the composite score were added to the model, the model's ability to accurately classify successful students was reduced to 65.9%, a decrease of 1.0%. Therefore, the model's ability to predict the likelihood of student success in introductory algebra decreased with the addition of both predictor variables.

The information found in the classification table was used to calculate sensitivity and specificity, which are then used in null hypothesis testing. Sensitivity, the ability of the model to correctly predict the number of successful students who were observed to be successful was 66.67%. Similarly, specificity measures the ability of the model to correctly predict non-successful students who were observed not being successful. The specificity of this model was 16.67%, which means that about 83% of the time the model identified a student as being successful when the student actually failed the course. These results suggest that the model is not a useful predictive model.

Table 18

Classification Table for Research Question 2

	Observed		Predicted: Success No	Predicted: Success Yes	Percentage Correct
Step 0	Success	No	0	126	.0
		Yes	0	255	100.0
	Overall Percentage				66.9
Step 1	Success	No	1	125	.8
		Yes	5	250	98.0
	Overall Percentage				65.9

Note. The cut score is .500. At Step 0 only the constant is included in the model. At Step 1 both predictor variables are included in the model.

In summary, a binomial logistic regression was performed to determine the effects of modality and a composite placement score on the likelihood that students in a UCCCD introductory algebra course would be successful. The model explained 2.7% (Nagelkerke R^2) of the variance in student success. The model's ability to correctly classifying the students in the introductory algebra decreased by one percent after composite placement and modality were added to the model. As a predictor, the composite score was not statistically significant (p = .078), while modality was statistically significant (p = .033). Hence, students who chose online instead of face-to-face had a reduction in their likelihood of success in the introductory algebra course. Stated another way, students who chose face-to-face would have 1.91 times greater odds of being successful in the introductory algebra course when compared to students in the online version. The inclusion of the composite placement score as a nonsignificant variable did not influence the results of multiple goodness-of-fit tests that indicated the model was a good fit for the data. The composite placement score, as a non-significant statistical predictor, was kept in the model because the research design, research question, and null hypothesis required inclusion of the composite placement score. As a reminder, the null hypothesis for RQ2 is that there is no significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course introductory algebra. While the model was statistically significant, $\chi^2(2) = 7.590$, $p < .05$, I determined that the lack of statistical significance of the composite placement score indicated that the null hypotheses cannot be rejected.

Additional Statistical Tests

The research questions for this study focused on the use of a composite placement score and modality for predicting the likelihood of student success. While no additional tests of the hypotheses emerged, I examined whether a model that used three different predictor variables (placement score for mathematics, placement score for reading comprehension, and modality) would improve predicting the likelihood of student success when compared to the original models for basic arithmetic and introductory algebra. The results were similar to the findings of my original study for the two research questions.

The second model for basic arithmetic was statistically significant, χ^2 (3) = 7.59, $p < .001$. The addition of the three predictor variables improved this model's ability to predict the likelihood of student success by 2.1%, which is an improvement of 1.3% from the original model. The results of this second model for basic arithmetic's indicated that the mathematics placement score and the reading comprehension placement score were statistically significant ($p < .05$), while modality was not statistically significant ($p > .05$)

for the second model (see Table 19). The comparison of the two models, original and the second, indicated a slight improvement in predicting the likelihood of student success with the second model. Both the variables for the mathematics placement score and the reading comprehension placement score were statistically significant, with reading comprehension being more statistically significant than mathematics, which seems reasonable as the composite placement score was statistically significant in the original model. The result indicated that reading comprehension (*OR* = 1.033, *p* = .000) was almost as strong of a contributor as mathematics proficiency (*OR* = 1.053, *p* = .004) when predicting the likelihood of student success for basic arithmetic.

Table 19

Variables in the Equation for the Modified Research Question 1 Model

	β	SE β	Wald's χ^2	*df*	Sig. *(p)*	Exp(β) Odds Ratio	95 % C.I. for Exp(β) Lower	Upper
Math Score	.031	.011	8.311	1	.004	1.031	1.010	1.053
Reading Comp. Score	.022	.005	15.841	1	.000	1.022	1.011	1.033
Modality	-.149	.299	.247	1	.619	.862	.480	1.549
Constant	-2.010	.528	14.499	1	.000	.134		

Note. Modality is for online compared to face-to-face.

The second model for introductory algebra was *nearly* statistically significant, χ^2 (3) = 7.809, *p* = .05 as compared to χ^2 (2) = 7.590, *p* < .022 in the original model. It was interesting that regardless of the model for introductory algebra, original or second, the addition of predictor variables reduced the model's ability to predict the likelihood of student success from 66.9 to 65.9 or by one percent. Modality was statistically significant in both models, *p* = .033 for the original model and *p* = .029 for the second model (see Table 20). When examining modality for both models, the results indicated that students in the face-to-face introductory algebra course were almost twice as likely to be successful as students in the online version of the course, because the odds ratio (*OR)* = 1.912 in the original model and *OR* = 1.976 in the second model (i.e., found by taking the inverse of the *OR* for each model as both *ORs* were reported as less than 1). Neither variables for reading comprehension placement score and mathematics placement score were statistically significant predictors of the likelihood of student success in either model for introductory algebra. As mentioned earlier, these results may be attributed to the misplacement of students into introductory algebra.

Table 20

Variables in the Equation for the Modified Research Question 2 Model

	β	SE β	Wald's χ^2	*df*	Sig. *(p)*	Exp(β) Odds Ratio	95 % C.I. for Exp(β) Lower	Upper
Math Score	.005	.008	.385	1	.535	1.005	.989	1.021
Reading Comp. Score	.010	.006	2.664	1	.103	1.010	.998	1.010
Modality	-.680	.312	4.759	1	.029	.506	.275	.933
Constant	-.247	.618	.159	1	.690	.781		

Note. Modality is for online (coded as 1) compared to face-to-face (coded as 0).

Summary

The original models used to predict the likelihood of success for basic arithmetic and introductory algebra indicated that the log odds of a student being successful was positively related to the composite score but negatively related to modality. In other words, the higher the composite score, the more likely the student will be successful. If two students have the same composite score, the student who chooses a face-to-face basic arithmetic course has 1.17 times greater likelihood of being successful than the student who chooses an online version of the course. Similarly, if two students have the same composite score, the student who chooses a face-to-face introductory algebra course has 1.91 times greater (almost double) likelihood of being successful than the student who chooses an online version of the course. Using multiple measures, I rejected the null hypothesis for the first research question (basic arithmetic), but did not reject the null hypothesis for the second research question (introductory algebra). However, as previously noted, while neither model was strong, the model for introductory algebra was the weakest of the two possibly due to the sample's data. In addition, reading proficiency was a statistically significant predictor of the likelihood of student success in an online basic arithmetic course, but not for introductory algebra. In sum, the findings showed that there was a significant and statistical difference in predicting the likelihood of student success with the use of a composite placement score only in the basic arithmetic DM course.

In Chapter 5 there is an extensive discussion of the implications of the binomial logistic regression results for each of the research questions. Also, limitations of the research and how the findings filled a gap in the literature are discussed. I also identified and discussed the key essence of this study and provided possible research questions for future researchers to consider and build upon my research.

Chapter 5: Summary, Recommendations, and Conclusions

Placement of community college students into DM courses is frequently based on a single mathematics placement score (Melguizo et al., 2016; Ngo & Kwon, 2015; Rodriguez et al., 2015). However, recent studies on placement policies/practices and student success in DM indicated that the relationship is more complex (Acosta et al., 2016; Scott-Clayton & Stacey, 2015). Improving student success rates in DM courses, specifically online DM courses, required looking beyond students' lack of mathematics proficiency.

The purpose of this quasi-quantitative research was to determine whether a change in UCCCD policy and practices for student placement into DM courses would improve predicting the likelihood of student success in online DM courses. After a review of the initial archival data provided by UCCCD, I concluded that a stratified sampling technique was the best method for identifying a sample population for each research question. The research design was a pre-experimental, static-group comparison research design, which compared a treatment group (online) with the control group (face-to-face). Binomial logistic regression models were used to examine the effect of a composite placement test and modality on predicting the likelihood of student success in online DM courses. The overarching research question for this study was to determine the extent that a composite placement score (i.e., the summation of the placement scores for elementary algebra and reading comprehension) could predict the likelihood of student success in the online DM courses of either basic arithmetic or introductory algebra.

The key findings of the research on basic arithmetic indicated a statistical and significant positive relationship between online student success and the composite placement score for basic arithmetic (β = .024, Exp(β) = 1.024, $p < .001$), and modality was not a significant predictor. The model also indicated that the addition of variables (composite placement score and modality) slightly improved (0.8%) the prediction of the likelihood of student success and that the model explained about 10% of the variance (Nagelkerke R^2 = .098). As a result of these findings, the null hypothesis for RQ1, which stated that there is no significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course basic arithmetic, was rejected. Using the modified model for RQ1, I determined that reading comprehension (Exp(β) = 1.022, p = 000) was almost as strong a predictor as mathematics proficiency (Exp(β) = 1.031, p = .004) of the likelihood of student success in a basic arithmetic.

The key findings of the research on introductory algebra indicated that the composite placement score was not a statistical and significant predictor of the likelihood of student success, while modality was statistically significant. As a result of this finding, the null hypothesis for RQ2, which stated that there is no significant difference in predicting the likelihood of student success with the use of a composite placement score for online DM course introductory algebra, was not rejected. The modified model for RQ2 also indicted that neither the mathematics placement score nor the reading comprehension was statistically significant. However, the results for modality indicated that students in an online introductory algebra course were less likely to be success than students in a face-to-face introductory algebra course, which represented a negative relationship between online as a modality and student success (β = -.648, Exp(β) = .523, $p < .05$).

Interpretation of the Findings

In this section, I discussed how the key findings confirmed, disconfirmed, or extended knowledge about online DM courses by comparing the findings of this research to the literature discussed in Chapter 2. I also reviewed the findings from the lens of bounded rationality theory, which examined the decision making process. This project's findings contributed to the knowledge gap in the domain of DM by further exploring student success in online DM courses.

Findings Related to the Literature

This study investigated whether a composite placement score and modality were predictive of UCCCD’s student success in DM courses of basic arithmetic and introductory algebra. A binomial logistic regression analysis found that the composite score, as a predictor, was statistically and significantly predictive of student success in the basic arithmetic course, while modality was statistically and significantly predictive of student success in the introductory algebra course. UCCCD leadership can use this evidence-based research to begin the conversation about updating the placement policy and practices, which currently only uses the mathematics placement score for placement into a specific DM course with no mention of modality options. The new policy should include providing students with information about the influence that the addition of reading proficiency and choice of modality contributes to their success. This type of information ensures students are making informed decisions that have the potential to contribute and not hinder their success in a DM course.

The findings of this study confirmed or extended the literature's reported institutional information on DM students. UCCCD indicated that 67% of first-time students require DM, which is similar to the statics reported by Okimoto and Heck (2015) who reported that nationally almost 70% of students were classified as academically underprepared for college-level courses require DM. Cullinane and Treisman (2010) reported that 32% of students in a developmental program required basic arithmetic and 27% required introductory algebra, which are lower than the findings of this research study. Of the targeted population (39,585 students), 42% required basic arithmetic and 58% required introductory algebra. This data indicated that a greater percentage of UCCCD students required DM courses than reported by Cullinane and Treisman.

The sample population (n = 767) had a success rate of 66% regardless of DM course or modality. For the sample population, face-to-face DM courses had a success rate of 86% and online DM courses had a 15% success rate. These findings confirmed Barnett and Reddy's (2017) conclusion that online DM students fail at a higher rate than students in face-to-face DM courses. The research findings of this study extended and confirmed the knowledge found in the DM literature.

An unforeseen result of my study was the confirmation and extension of results reported by Scott-Clayton et al. (2014) and Jaggars et al.'s (2015). Scott-Clayton et al. (2014) reported that a third of incoming community college students were mistakenly placed into DE courses, a result similar to mine for introductory algebra students. My results also extended the work of Jaggars et al.'s (2015) who concluded students were often misplaced into the highest-level DM course instead of a college-level mathematics course. My results also indicated that students in UCCCD's highest DM course were misplaced. Both of these researchers argued that these misplacements were the result of placement policies and practices. However, these authors failed to mention the role that student decision making had on misplacement.

The results of my study indicated that 7% or 27 students in the introductory algebra sample population should have chosen intermediate algebra (a college credited mathematics course) based on their mathematics placement score, but instead self-misplaced themselves into the highest-level DM course. These 27 students, whose placement scores qualified them for intermediate algebra, would have benefited from placement policy and practices that offered or required additional advising and/or information during the placement process to ensure the students were properly placed.

While the work of Jaggars et al. (2015) focused on misplacement of students into the highest DM course instead of a college-level mathematics course, my findings indicated an additional placement policy and practice problem. Findings from my study indicated that 23% of the introductory algebra sample participants (89 students) had placement scores below the range of 50 to 69 for a referral to introductory algebra. Based on their mathematics placement scores, instead of introductory algebra, these 89 students should have chosen basic arithmetic. The UCCCD placement policy and practices should have required that these 89 students receive additional advising and information prior to enrolling in introductory algebra.

Similar to Jaggars et al., (2015), I concluded that UCCCD's placement policies and practices contributed to DM students being misplaced. Additionally, it became apparent to me that UCCCD's placement policies and practices, which expects students to be enrolled in the appropriate DM course (i.e., based on mathematics placement score), was not followed by district campus admission advisors or faculty. In other words, 116 students were misplaced, not only by UCCCD policies and practices, but also by personal decision making on the part of the student. According to Simon's (1947) bounded rationality theory, which provided the theoretical framework for this study, students as decision-makers need timely and accurate information to make an optimal decision about their education. Simon also remarked that many students lack an understanding of how college works; thus, these students require institutional structures to guide their decision making. The findings of this study confirmed that placement into DM, regardless of level, is a complex endeavor. Thus, placement policies and practices need to be efficient, effective, and informative.

Statistical results for the RQ1, which focused on whether the composite placement score for students in basic arithmetic significantly and statistically influenced the likelihood of student success, indicated that the composite score was statistically significant ($\beta = .024$, $\text{Exp}(\beta) = 1.024$, $p < .001$). The composite placement scored added significantly to the model and its odd ratio indicated that for every point increased, a student's odds of success increased by a factor of 1.024 for online students in basic arithmetic. However, modality was not statistically significant ($\beta = -.154$, $\text{Exp}(\beta) = .857$, $p = .606$). This finding was similar to that of Nguyen (2015) who also concluded that self-selection of modality was typically not significant. The finding that the composite placement score was statistically significant lead to my decision to reject the null hypothesis for RQ1.

Using multiple measures of goodness-of-fit, I also determined that the predictive model developed for RQ1 was a good fit for the data even though the predictor variable modality was not statistically significant. This indicated that the RQ1 model could be used to predict the likelihood of student success. Therefore, I used the RQ1 model to calculate that a student in the online basic arithmetic course would need at least a composite score greater than 86. This score is reasonable as placement into basic arithmetic requires a mathematics placement score (based on the ACCUPLACER elementary algebra test) between 20 and 49, which means that the reading comprehensions score would provide the remaining points to reach 86. For example, a student with a mathematics placement score of 20 would need to place into the highest developmental reading course with a score of 66 (placement score range of 56 to 73). The interpretation of this calculation is supported by the work of Bailey and Jaggars (2016) who noted that most students in DM are also in another DE course. My study confirmed the logical idea that the higher the composite placement score the greater the likelihood a student has of being successful in the online basic arithmetic course.

Statistical results for the RQ2, which focused on whether the composite placement score for students in introductory algebra significantly and statistically influenced student success, indicated that the composite score was not statistically significant ($p > .078$). Therefore, because the composite score was not statistically significant, I was not able to reject the null hypothesis for RQ2. The misplacement of students into the introductory algebra course, as previously discussed, could have contributed to the reason the null hypothesis for RQ2 was not rejected. This means that the model cannot be used to predict the likelihood of student success in an online introductory algebra course at UCCCD.

When examining modality results for introductory algebra (RQ2), the results indicated that students in the face-to-face introductory algebra course were almost twice as likely to be successful than students in the online version of the course, because the odds ratio (*OR)* = 1.912 in the original model and *OR* = 1.976 in the modified model (i.e., found by taking the inverse of the *OR* for each model as both *ORs* were reported as less than 1). These results confirm the conclusion stated by Wolff et al. (2014) that student success rates in online DM courses were lower than the traditional face-to-face learning environment.

I also conducted additional logistic regression tests to examine the extent that reading comprehension, alone and not part of a composite score, had on predicting the likelihood of student success on either DM course (i.e., basic arithmetic and introductory algebra). As there is limited research on the influence that reading proficiency has on community college students' success in online DM courses, this additional testing added information to the knowledge gap in DM research.

This extension of my research indicated that the reading comprehension placement score as a single predictor variable (not as an addend of the composite score) was a statistically significant predictor of the likelihood of student success for only the basic arithmetic course (β = .022, Exp(β) = 1.031, p = .004). These findings are similar to those in my original analysis for RQ1, in which the composite score was statistically significant as well. In contrast, using the introductory algebra data, the results indicated reading comprehension was not statistically significant (β = .010, Exp(β) = 1.010, p = .103), which compared to my original findings using a composite score. Therefore, these findings suggest that reading comprehension had an influence as a predictor on the likelihood of student success in online basic arithmetic courses, but not necessarily for students in the online introductory algebra course. I am reluctant to conclude that reading comprehension does not have an influence on student success in an introductory algebra course because of the previously discussed concern about the misplacement of students in this course.

My findings support the work of Wolff et al. (2014) who concluded that mathematics and reading comprehension proficiencies along with modality were statistically significant predictors of student success in DM courses. My findings on basic arithmetic also support the suggestion made by Boatman and Long (2018), who wrote that students with a low reading comprehension placement score should first improve their reading proficiency before enrolling in an online DM course. Whereas, the number of students who self-misplaced themselves into the DM course of introductory algebra support the findings of many authors, including Wolff et al. (2014), who reported that placement policies and practices contribute to the low student success rates in DM courses.

Findings Related to the Theoretical Framework

Self-misplaced introductory algebra students demonstrated the importance of understanding the bounding rationality theory, which indicates that providing students with necessary information during the placement process results in students making an informed and optimal decision. The application of bounded rationality theory (Simon, 1947) explains that students struggle with gathering appropriate and timely information needed as they advance through the placement process. Within the context of community college, students referred to DM must decide on the course and the course modality without information about the influence that reading proficiency and modality has on their likelihood of success in an online DM course. For example, the students who made the decision to self-misplace themselves into introductory algebra could have benefited with information about enrolling in the appropriate DM course. This decision could have shortened their time in the DM sequence and moved them towards attainment of their academic goal, according to bounded rationality theory.

Findings from my study indicated there is a significant and statistical difference in predicting the likelihood of student success with the use of a composite score (i.e., the combined placement scores for mathematics and reading comprehension) for basic arithmetic students and with the choice of modality for introductory algebra students. Hence, basic arithmetic students, when provided information on their placements scores for mathematics and reading comprehension, could make an informed decision about which modality would increase their likelihood of being successful in that class. While, introductory algebra students could make an informed decision when provided information about the relationship between success and modality. The application of Simon's (1947) bounded rationality theory indicates that during the placement process students need information on the influence that placement scores and modality has on their enrollment choices. Students need to understand that the decisions made during the placement process influence their attainment of life and academic goals.

Limitations of the Study

This research was limited to community college students who placed into a DM course using ACCUPLACER mathematics placement scores. These research findings are generalizable to community colleges and universities that use ACCUPLACER for placement purposes. The results are generalizable to the colleges within the UCCCD system because data from nine of the ten campuses was used in this study and all the colleges used the UCCCD's cut score guidelines for placement into DM courses. I had a concern about the validity and reliability of the data used for the introductory algebra course due to the wide range of placement scores for mathematics. I attributed this wide range of scores to students' choice of DM course not suggested by the placement scores, specifically in the introductory algebra course. This wide range of mathematics placement scores for the introductory algebra course could have contributed to the findings and the result of not rejecting the null hypothesis for the second research question. A stratified random sampling technique was used to identify the sample populations from the targeted population. The use of this sampling technique reduced the bias of the sample and allowed for the use of a smaller sample for each RQ. Students without a score for elementary algebra were excluded from the sample populations for basic arithmetic and introductory algebra. Further, this study was limited by the use of archival data and by the lack of the use of true experimental design, which does not affect the validity or generalizability of the findings (Campbell & Stanley, 1963).

Recommendations

Future studies should replicate this research using regression discontinuity, which could provide additional information about students at the margins of the cut scores to determine the influence of reading comprehension on possible placement into the higher-level online DM course. Placement into a higher-level DM course would potentially allow the student to take their first college level mathematics course sooner, thus reducing the time and money spent on DM courses. Another recommendation would be repeat this study but limit the target population to students who followed the placement policy for each DM course, which could provide evidence of the influence that placement policy and student decision making has on student success. A final recommendation would be to add writing as a predictor variable of the likelihood of success as students in an online course communicate with the instructor and peers through writing.

Implications

Positive Social Change

The findings of this research foster a positive social change that is good for the community college district's community and its stakeholders. The suggested changes to the placement policy and practices include not only the findings from this research, but also the addition of informing students of the likelihood of success in an online DM course based on their reading comprehension score and choice of modality. These changes have the potential of improving success rates for students, which improves persistence (continued enrollment) and transfer rates for the community college district. Students who complete a program or earn a degree represent an asset to the local community (Boatman & Long, 2018; Dynarski & Scott-Clayton, 2013). Improving student success rates in online DM courses, or any online course, increases students' attainment of their academic and ultimately their life's goals.

Theoretical Implication

From a positive social change view, bounded rationality theory suggested that students who make informed decisions improve their likelihood of success in a DM course. Scott-Clayton (2011b) posited that community college students referred to DM make many complex decisions, often without the assistance of a well-informed advisor, during the registration process. Students, as decision-makers, require access to reliable placement advice and guidance (Harrison, 2017). Both Simon (1957) and Scott-Clayton (2011b) remarked that decision-makers (e.g., students) are often bounded by the failure of institution to provide timely, relevant, and useful information. Bounded rationality theory (Simon, 1957) suggested that improving decision making is required at all the organization levels. For a community college, this would include the student level, policy and practices level, and advisement level. Bounded rationality theory provided the lens of what variables to select for my study. These variables were ACCUPLACER placement scores, modality, and student success. Placement scores, being the starting point of the placement decision making for students.

Currently, UCCCD students are referred to a specific DM course and then self-select the modality. Simon (1957) proposed that with more information, students, as decision-makers would make a more optimal decision. For DM students, understanding the influence that their reading comprehension score, as a part of their composite score, has on their likelihood of success in a basic arithmetic course would encourage them to choose online only if this modality was the best fit for their learning needs and learning style. Students enrolling in introductory algebra need to understand that their choice of modality influences their success. Based on the bounded rationality theory (Simon, 1976), students would not settle for a satisficing solution but would optimize their chance of success if given the information about reading comprehension's and modality's influence on their success in a DM course.

Simon (1947) and Scott-Clayton (2011a) argued that the lack of institutional structure, placement policies, and practices, when coupled with the students' lack of cultural capital often results in students making decisions that create three problems-misplacement, delay in enrolling, and dissatisfaction with their decisions. Scott-Clayton observed that due to the lack of institutional structure, DM students who had an unpleasant enrollment experience and an unsuccessful semester often failed to return for the following semester. Huntington-Klein, et al. (2015) posited that community college leadership should consider a placement policy that limits enrollment in online courses to those students who are more likely to be successful. The findings of this research provide information that could assist UCCCD's leadership in beginning a dialog about the institutional structure associated with placement policy and practices. This dialog should result changes in placement policy and practices to assist students in making a more informed decision on the choice of DM course and modality. As a result of making informed decisions, students who require a DM course will have a positive community college experience, reach their academic goals in a reasonable amount of time, and enter the local community workforce equipped with the skills and knowledge needed to be successful (Melguizo et al., 2016).

Recommendation for Practice

Helping underprepared students understand their academic gaps and the options for courses is typically the role of academic advisors. Academic advisors, when fully informed of the placement policy and practices, are able to provide not only guidance, but also timely and appropriate information during the placement process. However, Donaldson, McKinney, Lee, and Pino (2016) argued that community colleges students who require DE courses are less likely to be proactive and seek guidance from academic advisors. Therefore, Donaldson et al. (2016) recommended that academic advisors and faculty members practice an advising model where students are expected to take advantage of advisors during the placement process. I agree with these findings because of this study's findings that 30% of the introductory algebra sample population self-misplaced themselves into introductory algebra.

In light of the results of this research, community college administrators and mathematics faculty should be motivated to review their current placement policy and practices. UCCCD mathematics faculty should be active participants in student decision making about by providing students with timely and appropriate information. This information needs to include the influence that placement scores and modality have on the likelihood of student success in DM courses. To better advise students, academic advisors and mathematics faculty need to offer students information on how their reading comprehension placement score influences their success in an online basic arithmetic course and how their choice of modality influences success in an introductory algebra course. In applying bounded rationality theory to academic advising, underprepared students require assistance with decision making due to their lack of receiving structured information, low cognitive understanding of the situation, and time pressures.

Conclusion

A common theme in the DM literature is the negative impact that the time spent in a DM course sequence has on students enrolling in their first college-level mathematics course, their transfer to a 4-year postsecondary institution, and their attainment of a college degree. The current placement policy and practice among many community colleges is to refer students to DM courses based solely on a single mathematics placement score. Scott-Clayton (2011b) asserted that students, many of whom are first generation enrolling at a community college, need structure and academic guidance to understand their course options and avoid course placement errors. Simon's (1947) bounded rationality theory indicated that students, when provided with timely and appropriate information, make informed and optimal decisions about their education. Therefore, the key to improving student success with the use of a composite placement score requires understanding that students, as decision-makers, need access to timely and appropriate information during the placement process. In addition, institutions should ensure that placement policies and practices are followed by academic advisors, faculty, and students to improve success in DM courses.

Although the findings of this quasi-experimental study were mixed, they contribute to the understanding of how decision making at the institution and student levels influence student success rates in DM courses. The findings of this study made four contributions to the literature by confirming and/or extending the existing body of literature on traditional and non-traditional first-time community college students' success in individual DM courses. First, I concluded that a composite score (based on ACCUPLACER placement scores for mathematics and reading comprehension) statistically and significantly predicted the likelihood of student success in an online basic arithmetic course, but not for an online introductory algebra course. Second, the results of the study indicated that the reading comprehension placement score alone could statistically and significantly predict the likelihood of student success in an online basic arithmetic course. Thirdly, that modality was a predictor of the likelihood of student success in an online introductory algebra course, but not basic arithmetic. Finally, students misplaced themselves into DM courses, specifically introductory algebra (the highest DM course at UCCCD), regardless of placement policy and practices. The positive social change aspect of my study was framed by the fours findings noted above, which indicated that community colleges could facilitate improving student success rates in DM course that in turn would increase students' attainment of their academic and life's goals. Therefore, improving student success rates in DM courses benefits all stakeholders, which includes the community college, the local community, and the students.

While the findings of this study were not as robust as had been anticipated, they should encourage community college leaders and mathematics faculties to begin the conversation about adding reading proficiency and modality to DM placement policies and practices, as well as, stimulate further research. Also, students enrolling in a DM course should be required to seek advice from academic placement advisors and/or mathematics faculty. I concluded that students' lack of knowledge about the influence of reading comprehension and modality on success in an online DM course creates a potential barrier to the attainment of the academic skills needed for meeting their educational goals at a reasonable cost of money and time.

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