


Spring 5-12-2018

Developmental Mathematics: A Quantitative Investigation of Instructor Classification as Related to Student Success

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Developmental Mathematics: A Quantitative Investigation of Instructor Classification as Related to Student Success

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**DEVELOPMENTAL MATHEMATICS: A QUANTITATIVE INVESTIGATION
OF INSTRUCTOR CLASSIFICATION AS RELATED TO STUDENT SUCCESS**

by

Brittany A. Fish, B.S., M.S.

Presented to the Faculty of the Graduate School of

Stephen F. Austin State University

In Partial Fulfillment

of the Requirements

For the Degree of

Doctor of Education

STEPHEN F. AUSTIN STATE UNIVERSITY
(May 2018)

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ABSTRACT

The purpose of this quantitative study was to examine what type of predictive power exists between an instructor's employment classification, student gender, student race, and first-generation status on a student's academic success in developmental mathematics, as measured by final semester grades at a regionally comprehensive state university in Texas between fall 2013 and spring 2017. Data were collected from the institution under study and the sample population included 1932 unique student observations. The data collected in this study were analyzed through a binary logistic regression model to determine whether an instructor's employment classification, student gender, student race, and first-generation status could predict academic success in developmental math. The results of this study showed that a correlation does exist between an instructor's employment classification, specifically as related to Graduate Teaching Assistants and Adjunct Instructors in being statistically significant to a student's success in developmental mathematics. Additionally, student race, student gender, and first-generation status showed that a correlation does exist in predicting a student's success in developmental mathematics, all of which were found to be statistically significant. The findings and conclusions of this study have implications for post-secondary math educators and higher education administrators.

ACKNOWLEDGEMENTS

I would first like to acknowledge my mother and father. I am who I have become because of the foundation my parents set for me as a young child. My father and mother helped me understand the importance of hard work, perseverance, and faith in striving for nothing less than the goals I set for myself. These qualities assisted me immensely through this process. My husband, Gavin Fish, was nothing less than the most loving, patient, and supportive companion through these past three years. My son, Connor Fish, while he was too young to remember this phase of our lives, I hope he remembers the quality time he got to share with his grandparents as they dedicated their weekends to babysit while I was in class or writing.

Next, I would like to acknowledge the faculty of the Educational Leadership Doctoral Program. Each of you played a special role in shaping me into the professional I am and I will forever be grateful for your mentorship. Most importantly, I would like to acknowledge my dissertation chair, Dr. Patrick Jenlink. His support, guidance and genuine care for my development as a scholar-practitioner leader has provided me with the necessary tools needed in moving forward with my growth in higher education.

Finally, I would like to acknowledge the members of Cohort 19. Our time spent together through this process is one that I will always treasure. There is no other group of individuals I would have want to have gone through this process with.

DEDICATION

“For I know the plans I have for you,” declares The Lord, “plans to prosper you and not to harm you, plans to give you hope and a future.”

To my children...

Always be authentically you.

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CHAPTER I

Introduction to the Study

Theoretical Framework

College readiness initiatives require students who do not meet standardized test scores to enroll in developmental coursework as they transition into higher education. As recently as October (2016a), a Texas Higher Education Coordinating Board report found that 13% of students enrolling in a Texas university showed a need for developmental interventions. The purpose of remediation in higher education has been questioned in recent years, yet the continued need for remedial coursework continues to rise (Bonham & Boylan, 2011). Sparks and Malkus (2013) compiled data for the National Center for Education and found that the number of first-year undergraduate students enrolled in remedial coursework at public institutions increased to 23.3% during 2007-2008.

According to Brier (1984), there has been much controversy surrounding the education of the underprepared student in higher education. However, there are several negative implications of not providing an equitable educational opportunity, such as unemployment, low-wage jobs or welfare, and incarceration (Waycaster, 2010). Additional consequences are a delay in graduation, students forced to pay full tuition

costs for the required developmental coursework, and the hours accumulated in attempting to complete development requirements that cut into a student's limited excessive hours, which could potentially pose additional financial implications to the student later on (Bettinger, Boatman, & Long, 2013). As one of the major challenges facing institutions of higher education, universities are attempting to address the expanded need for developmental education programs.

The National Center for Education Statistics report showed that 72% of institutions reported offering at least one developmental math course, making developmental math the most likely developmental course to be offered by colleges (Fike & Fike, 2012). Successful remediation programs have been shown to provide educational benefits, as successful students tend to continue on into regular courses and engage in collegiate activities (Waycaster, 2010). Research suggests that students who do enroll in and successfully complete remediation requirements for mathematics continue on to be just as successful in a college-level math course as those who were not required to enroll in a remedial math course (Bahr, 2008). However, in a nationwide study at two-year and four-year institutions, Attewell, Lavin, Domina, and Levey (2006) reported that only 30% of students pass all of the developmental math courses in which they enroll. In Texas alone, only 28.5% of students who required developmental coursework in 2010 earned a bachelor's degree within six years (Texas Higher Education Data, 2017). However, the Texas Legislature appropriated \$200 million in General Revenue Funds during the 2015-2016 biennium for instructional cost of developmental education and public institutions of higher education (Legislative Budget Board, 2017).

The question that this appropriation raises is whether or not the purpose of remediation in higher education is to develop students in reaching academic standards and goals. If the purpose of remediation is to develop students in reaching academic standards, then why are the vast majority of students unable to successfully complete developmental mathematics?

Wambach, Brothern, and Dikel (2000) proposed the framework of developmental theory in which the concepts of self-regulation, demandingness, and responsiveness are united “. . . to organize, explain, and predict useful techniques for practitioners . . .” (p. 2). The theory is grounded in the ideology that self-regulation should be a main objective of developmental education (Kinney, 2001). Zimmerman, Bonner, and Kovach (1996) defined self-regulation as how one might generate thoughts, feelings, and actions related to the attainment of educational goals. Self-regulation relating to developmental education plays a vital role in molding a student’s perception of academic success. Many students who place into developmental education courses develop a defeatist attitude. Schnee (2014) found that as students failed a placement exam and were enrolled in developmental education, many developed anxiety and began to question their ability to be successful in higher education.

Wambach et al. (2000) intertwined the development of a student’s self-regulation with the demandingness and responsiveness of the course, both of which are identified as expectations set forth by an instructor. Kinney (2001) identified demandingness in the context of developmental education as performance expectations. This entails a participative learning environment, attendance for each class session, and the utilization

of tutoring resources to ensure assignment submissions meet instructor expectations. Demandingness in developmental education streamlines to the responsiveness of an instructor to provide appropriate feedback that is personal, timely, and beneficial towards student mastery (Kinney, 2001). By understanding and implementing these efforts, instructors of developmental education should be able to foster student-regulation in developing self-efficacy in a developmental course.

However, in a study conducted by Weissman, Bulakowski, and Jumisko (1997), of 116 colleges and universities “. . . only a small percentage conducted any systematic evaluation of their remedial education programs . . .” (p. 10; Bettinger & Long, 2009). Grubb (2001) found that the effectiveness of developmental programs has not been an issue considered, as most research focuses on student attributes in relation to academic success, yet the few evaluations that have been conducted of remediation programs prove to be useless. Researchers of developmental education have provided an abundance of data evaluating a student’s ability to persist past developmental mathematics based on demographic variables. Additionally, there has been a dramatic increase in the amount of part-time students who are enrolled in developmental mathematics (Abraham, 1992). Short (1996) suggested that these variables are the strongest predictors of student success in developmental mathematics. With research relying on student attributes to identify student success in developmental courses, there is a need for institutions to reflectively consider their own attributes, such as instructor quality based on employment classification, as to identify areas for needed improvement.

Statement of the Problem

According to the Texas Higher Education Coordinating Board, the summary of developmental education programming survey conveyed results that institutions minimally required developmental educators to have at least a Bachelor's degree and nearly half of the institutions did not require professional development for these educators (2016b). Students with developmental needs tend to have multiple learning deficiencies (Burley, Butner, & Cejda, 2001; Rutschow et al., 2011) and struggle with juggling multiple educational and personal responsibilities in comparison to the university student population (Ashby, Sadera, & McNary, 2011). With college readiness standards set to increase once again, institutions are leaving behind a student population in most need of intensive instruction utilizing differentiated pedagogical practices by continually employing lower level instructors to oversee developmental courses.

While studies have found that attrition rates of developmentally liable students can be attributed to high school GPA and ethnicity (Feldman, 1993; Murtaugh, Burns, & Schuster, 1999) and are common characteristics of the developmental population (Ashby et al., 2011), there has been no consistent results reported in relation to the employment classification of developmental mathematics instructors and student success rates. Thus, the problem addressed in this study was the effect of instructor employment classification on a student's academic success in developmental mathematics during 2013-2017 at a four-year state institution of higher education in Texas.

Purpose Statement

The purpose of this study was to determine what type of predictive power exists between an instructor's employment classification and a student's gender, race, and first-generation status, as measured by final semester grades in developmental math. A binary logistic regression statistical analysis was used to determine if a relationship existed and which variables were the best predictors of academic success in developmental mathematics. According to Garson (2014) the utilization of binary logistic regression is the appropriate method to be used when the dependent variable is dichotomous and the independent variables are of any type.

Research Questions

This study used a binary logistic regression model to determine if there was predictive power between instructor employment classification, student gender, race, and first generation status on academic success in a developmental mathematics course. The criterion variable in this study was the academic success in a developmental mathematics course while the predictor variables include instructor level, student gender, race, and first generation status.

The following questions were used to design and guide the assessment of the relationship:

1. Does an instructor's employment classification predict a student's academic success (receive a grade of C or better) in developmental mathematics?

2. Does an instructor's employment classification and a student's gender predict a student's academic success (receive a grade of C or better) in developmental mathematics?
3. Does an instructor's employment classification and a student's race predict a student's academic success (receive a grade of C or better) in developmental mathematics?
4. Does an instructor's employment classification and a student's first-generation status predict a student's academic success (receive a grade of C or better) in developmental mathematics?

Significance of the Research

Developmental mathematics courses were designed to provide equitable opportunity for less equipped students to achieve a degree in higher education. However, there has been considerable debate about the under preparedness of these students. Many students enroll in developmental mathematics per state requirements, but find themselves unable to reach their goals as the course that was supposed to help develop them towards academic success actually serves as an immovable barrier. According to Bonham and Boylan (2011), developmental mathematics proves to be the hardest course to pass in all of higher education, including four-year universities. The Noel-Levitz (2006) U.S. Department of Education Report found that out of all postsecondary courses, developmental math has the highest failure rate.

With minimal pass rates, many initiatives have been developed to improve the success rates of developmental mathematics. Boggs, Shore, and Shore (2004) explored

the use of master learning as a teaching strategy, while Acee (2009) evaluated the integration of learning strategies and math study skills. Additionally, other researchers have considered the use of active learning approaches such as cooperative learning and its impact on student success in developmental math (Barkley, Cross, & Major, 2005). Overall, institutions have attempted to meet the individualized needs of each student by offering non-course based options to assist in identifying a student's weakness in order to strengthen that area through tutoring, supplemental instruction, or labs (Texas Higher Education Coordinating Board, 2016a).

While institutions and instructors are diversifying the way developmental math is taught to students, what has not changed is the reliance on under qualified instructors in teaching developmental math. Many instructors for developmental math are hired as part-time instructors (Burgess & Samuels, 1999). This trend is quite evident at community colleges. Research conducted by Penny and White (1998) suggest, “. . . little empirical evidence has been offered to substantiate the effect that faculty characteristics have on developmental student achievement . . .” (p. 2). Ultimately, research on students with developmental requirements in relation to instructor qualities and their success rates is very limited even though this has been an interest to administrators and developmental education researchers (Esch, 2009). As developmental needs continue to expand, it is important for institutions to develop a better understanding of how instructor qualities play a role in a student's success in developmental courses in order to address equity concerns related to degree attainment.

Assumptions

This study made the following assumptions:

1. Data collected from the institution studied were accurate and valid.
2. The placement of each student in the appropriate developmental math course was accurately based on standard criterion.
3. The variables selected in this study explained student success in developmental mathematics.

Limitations

A limitation of this study was the small sample size for some ethnic, gender, or first generation student groups in determining an impact of instructor qualities on student success in developmental math. Additionally, an instructor's employment classification as coded in the university system may not necessarily have appropriately represented the qualifications or experience one might have had in teaching developmental mathematics. Furthermore, the small sample size of instructor employment classification can be considered a limitation. Finally, the findings of the research cannot be generalized outside of the institution studied.

Delimitations

A delimitation of this study was the time frame selected in which the data were collected. Due to policy regulations relating to the limited use of end of course exams for remediation exemption, the study collected data from the years 2013-2017. Additionally, this study focused on one regional state institution of higher education in Texas, which delimits the population studied. Another delimitation of this study was that the data only

considered students who were enrolled in developmental mathematics (MTH 099) for the first time to avoid participants being counted twice due to re-enrollment. Finally, in alignment with the purpose of the research study, the variables selected of the population studied assisted in identifying the best predictor of a student being successful in developmental math in relation to the instructor's employment classification.

Definitions

Throughout the study, the researcher used several terms specific to the study. In order to ensure the terms are understood as they are intended for this research, conceptual definitions are provided for the reader to develop meaningful understanding of the language used.

Adjunct faculty.

Adjunct faculty members are educators that are employed by an institution part-time, and are usually required to teach overloads or courses that tenured faculty members do not teach (Fulton, 2000). For the purpose of this study, adjunct faculty are defined by the institution that is studied as full-time or part-time positions that are contracted out on a semester basis (Stephen F. Austin State University, 2017).

College-level mathematics.

College-level mathematics entails credit-bearing coursework offered through an institution of higher education that, if completed successfully, can be applied towards the number of hours required for a degree (THECB, 2012).

Developmental mathematics.

A pre-requisite course required for students as an intervention that were assessed as substandard in mathematics based on the Texas Success Initiative Assessment. The course(s) are designed to enhance students' foundational knowledge of mathematic models to complete college-level mathematics courses successfully (Brothern & Wambach, 2004; THECB, 2008).

First-generation.

For the purpose of this study, first-generation students are identified as those whose parents do not hold a baccalaureate degree (Ward, Siegel, & Davenport, 2012).

Instructor.

According to THECB (2012), an Instructor is “a faculty member of an institution of higher education who is tenured or is on tenure-track and who does not hold the rank of assistant professor, associate professor, or professor” (p. 40). As defined by the institution that is studied, an Instructor must minimally hold a master's degree in the field in which the individual is teaching (Stephen F. Austin State University, 2017).

Lecturer.

The institution studied in this research defines a Lecturer as a full-time, nine-month faculty member who does not hold a terminal degree (Stephen F. Austin State University, 2017).

Student success.

Student success in a developmental mathematics course is defined as a student earning a final grade of 70% or higher in making the student eligible to enroll in the next

level of developmental math or a college-level mathematics course (Dahlke, 1974; Texas Administrative Code, n.d.).

Teaching assistant.

A teaching assistant, as defined for the purpose of this study, is a graduate student who is employed part-time to serve as the lead instructor of the assigned course (Shannon, Twale, & Moore, 1998; Stephen F. Austin State University, 2017).

Texas Success Initiative.

Originally identified as the Texas Academic Skills Program, the Texas Success Initiative was adopted by Texas Legislature effective September 1, 2003 to enhance to previous college-readiness program. The initiative requires a student to show academic proficiency through the completion of an assessment in reading, writing, and mathematics when entering a public institution of higher education in Texas (THECB, 2016c). Each student that does not meet the college-readiness benchmark on the assessment is required to enroll in the appropriate developmental courses in order to develop proficiency (THECB, 2016c).

Organization of the Study

Chapter I provided an overview of the study, research questions, definitions related to developmental education in higher education, as well as limitations and delimitations of the research. Additionally, Chapter I provided the purpose of the study as to determine if a relationship exists between an instructor's employment classification and a student's academic success in developmental mathematics, as measured by final semester grades, student gender, race, and first generation or non-first generation status.

Chapter II includes a review of related literature, such as historical perspectives of developmental education, an overview of research related to faculty academic rank in relation to teaching at-risk student populations enrolled in developmental education, and recent research related to student success in developmental mathematics. Chapter III provides an overview of the methodology of the study, along with a discussion of the methodological design. The findings of the research study are discussed and analyzed in Chapter IV. Chapter V provides a summary of the study with implications for educational policy related to developmental education in higher education, as well as suggestions for further research.

CHAPTER II

Literature Review

Introduction

The purpose of this study was to determine if a predictive power exists between an instructor's employment classification and a student's gender, race and first-generation status, as measured by final semester grades in developmental math. Defining a metric of success as students enter and exit higher education has gained currency in retention efforts as a way to identify critical points in a student's collegiate career path (Polk-Conley & Squired, 2012). One indicator to be considered is a student's success in developmental courses.

Attewell et al. (2006) suggested that colleges instituted developmental courses in order to manage the student population that came from poor performing high schools. Leinbach and Jenkins (2008) discussed the importance of students seamlessly transitioning from developmental to college-level courses and how doing so is empirically linked to a student's ability to reach degree completion. Developmental policies often act as a gatekeeper to higher education, as well as serve as quality control for students who cannot successfully complete remedial requirements since they have a greater chance of not being retained by the university. According to Snyder and Dillow

(2011), seventy-five percent of public-four year institutions in the nation offer remedial education opportunities. This is in direct reflection to the many high school students who enter post-secondary education underprepared to academically excel in college-level courses.

In 1994, Umoh, Eddy, and Spalding found that the majority of the students who enrolled in a developmental mathematics course did not enjoy the class, nor did they feel intellectually challenged by course materials. Even looking forward nearly twenty-one years, Pruett and Absher (2015) stated that developmental students have the highest attrition rate compared to other student populations. In order to address the attrition and lack of engagement among developmental students, institutions have responded by creating learning communities, intrusive academic advising efforts, and tutoring (Bettinger, Boatman, & Long, 2013). To develop a holistic understanding of developmental math and its place within higher education as related to the purpose of this research, this literature review will provide a historical understanding of developmental education, encompass a thorough foundation of the assessment, placement, and sequencing of developmental mathematics in the Texas higher education system, as well as consider the role of faculty in the classroom and student characteristics that may interplay in one's success in a developmental math course.

History of Developmental Education

The term “developmental education” became prominent and widely used during the 1970s among those who worked within the profession as a way to create the mindset that all students could develop their academic skills (Arendale, 2002; Boylan & Bonham,

2007). During the 1970s and 1980s, developmental education began to gain recognition within the field of academia as the National Association of Developmental Education earned funding from the W.K. Kellogg Foundation (Cafarella, 2014). The National Association of Developmental Education sponsored the nation's first professional development education program that allowed educators to earn a certification within the field of developmental education (Boylan & Bonham, 2007).

In 1984, the U.S. Department of Education began to acknowledge national research regarding developmental education as the National Center for Education and Statistics developed a report related to developmental education, and journals such as the *Journal of Developmental Education* and *Research and Teaching in Developmental Education* were releasing publication on the academic matter (Boylan & Bonham, 2007). The National Association of Developmental Education conducted the first national study related to developmental education in 1980, which contributed to “. . . improving practices in the field and enhancing the professionalism of developmental educators . . .” (Boylan & Bonham, 2007, p. 3). However, a turn occurred as the 21st century approached and developmental education became less of a priority for many four-year colleges and universities, as officials claimed programming was too costly and offering such courses diminished the standards of higher education institutions (Arendale, 2002). Jacobs (2012) found that since 2007 over a dozen states determined it necessary to restrict funding for four-year institutions to offer developmental courses in order to refer students to community colleges, as those institutions were viewed to be more equipped in serving underprepared populations.

In 2003, the initiative *Achieving the Dream: Community Colleges Count* was developed by private foundations and community college experts in order to address student success and to improve graduation rates at community colleges, as developmental education was found to be a contributing factor affecting students' ability to persist (Ashburn, 2007). The initiative focused on students of color and those coming from low socio-economic backgrounds in order to identify academic gaps in addressing the needs of these student populations to propagate student success. As an extension of this effort, in 2009 the Gates Foundation worked with the Lumina Foundation in researching models for developmental education, in which it has been reported that \$110 million dollars was donated towards this effort from the Gates Foundation (Ashburn, 2007). These funds helped create the Developmental Education Initiative grant which allowed community colleges to utilize funds in redesigning current developmental education programs in order to find ways to assist students through the developmental pipeline quicker, as related to the assessment, placement, and sequencing processes (Collins, 2011).

Developmental Math Education in Texas Higher Education

As a nationwide effort to increase college enrollment, institutions have provided developmental education as a way to enhance the skills of the underprepared student populations. In providing these resources to students, researchers have observed the lack of national standardized processes that should occur as a student is assessed and placed in developmental education (Bell-Ellwanger, King, Jr., McIntosh, 2017). In the state of Texas, however, the Texas Education Coordinating Board developed processes that all

state institutions should follow when assessing and placing a student in developmental education.

Assessment, placement, and sequencing.

Researchers have found that the assessment and placement of students into developmental mathematics can stem from a number of reasons. As students transition into higher education within the state of Texas, they are assessed on SAT, ACT, and STAAR test scores to determine college-level readiness (Waycaster, 2010). If a student does not meet the required scores to be placed in college-level mathematics, the student is then required to test on the Texas Success Initiative Assessment. The Texas Success Initiative Assessment is a placement exam that determines a student's level of college-readiness in math, reading, and writing. Bettinger et al. (2013) found that several states began administering a placement exam as early as tenth grade to allow ample opportunity for students to place out of collegiate developmental coursework. Additional research has shown that roughly ninety-two percent of institutions use some form of a standardized placement exam to enroll students in developmental courses (Bettinger et al., 2013). Yet, how students are placed in developmental courses vary from state to state and even from college to college (Boylan, 2009). For example, depending on the student's raw test scores, an institution may decide to mainstream the student into college-level coursework while providing an appropriate amount of learning assistance (Boylan, 2009). Additional research has suggested that colleges are too quick to enroll students in developmental courses without considering further examination (Bettinger et al., 2013).

In order to overcome the quick enrollment of students into developmental courses, Boylan (2009) advocated for the evaluation of non-cognitive student factors that may affect a student's ability to succeed, such as attitude toward learning, willingness to seek help, motivation, autonomy, and how the campus and course are integrated. The non-cognitive factors have been shown to be equally important as one's cognitive abilities when it comes to a student's success in developmental education, especially in students who have weaker cognitive skills (Sedlacek, 2004).

The placement model proposed by Boylan (2009) is titled the T.I.D.E.S. approach, which stands for targeted intervention for developmental education students. This placement process for assigning students into developmental courses utilizes data and evaluates multiple student variables to streamline incoming students, rather than relying solely on a cognitive assessment. An argument for such an approach has shown that non-cognitive and cognitive factors complement each other in a student's ability to be successful (Maxwell, 1997; McCabe, 2003). Additional research supports this placement ideology as it has been found that enrolling students in developmental courses when their test scores were under-representative of their abilities often caused a sense of discouragement to the students (Scott-Clayton & Rodriguez, 2012). Another consequence is that collegiate level enrollment has been found to be restricted for developmental students at more than four-fifths of campuses until the student has successfully completed remedial courses (Bettinger et al., 2013).

Institutions have not streamlined the developmental placement process to holistically evaluate college-readiness on a student-by-student basis. The difficulty in

implementing such an approach is the additional knowledge that would be required of academic advisors in evaluating student demographics to determine appropriate placement and intervention plans (Boylan, 2009). While this placement approach seems to create a paradigm shift in the advisor role, it deliberately attempts to create pathways for students to enroll firstly in college coursework in bypassing remediation with targeted interventions and appropriate academic and student support services.

Depending on the student's score on a placement exam, the student may be required to enroll in one of several levels of developmental mathematics in order to consider the student college ready (Boylan 2009; Waycaster, 2010). In considering developmental mathematics specifically, many institutions offer remedial arithmetic, developmental algebra 1, and developmental algebra 2. Sequencing success is highest for students who are placed in the last level of developmental mathematics, rather than the low sequencing success rate of seventeen percent of students who are placed into the lowest level of developmental math (Bettinger et al., 2013).

Researchers in the field of developmental education have agreed that the most successful developmental programs conduct continual mandatory assessments of developmental students in order to accurately depict a student's progression (McCabe, 2000; Roueche & Roueche, 1999; Saxon & Morante, 2014). In identifying this trend, educators and higher education administrators have begun to address the question of redesigning developmental courses.

Zachary and Schneider (2011) considered redesign efforts as four broad types. Some reforms look at shortening the time students spend enrolled in developmental

courses, some reforms include an integration of developmental coursework with college-level coursework, and other reforms consider non-course based options such as tutoring and advising interventions. Boatman (2012) used a regression discontinuity research design to evaluate the effect of a redesigned developmental math course on student success. For those students enrolled in the redesigned course, they had more positive outcomes than similar students who did not participate in a redesigned developmental math course. Bettinger et al. (2013) also identified positive effects on student success from institutions that redesigned remediation by mainstreaming students into college-level courses.

In considering the assessment, placement, and sequencing of developmental mathematics in higher education, institutions face challenges on how to appropriately assess and enroll students to maximize their potential success in a college level math course. The findings highlighted through course redesign efforts showcased a need for evaluating and improving remedial placement policies. With developmental enrollment rates increasing in higher education as college-readiness standards increase, it is important that developmental education is evaluated on its current level of effectiveness to identify needed areas of improvement.

Effectiveness of Developmental Education

There have been several studies that question the effectiveness of developmental education (Bailey, 2009; Calcagno & Long, 2008; Martorell & McFarlin, 2011). Calcagno & Long (2008) and Martorell & McFarlin (2011) argued against educational policies related to remediation as unhelpful, as their findings suggest limited benefits of

remediation programming. Some research has even gone as far as to highlight the negative effects remediation has on student outcomes (Boatman & Long, 2010; Calcagno & Long 2008; Martorell & McFarlin, 2011). Boatman and Long (2010) specifically found that students assigned developmental courses had fewer credits accumulated and had lower college completion rates than students of similar academic skill-set.

There has been evidence, however, to support the effectiveness of developmental education as having a positive impact on degree completion (Attewell et al., 2006; Bettinger & Long, 2005, 2009). Studies have proposed that the cause of poor educational outcomes was not related to the student's placement in developmental education, but instead was a result of the underlying weak academic preparation received at the secondary level. Boatman and Long (2010) stated, “. . . remedial and developmental courses help or hinder students differently depending on their level of academic preparedness . . .” (p. 4). This aligns with Bonham and Boylan (2011) who advocated that improving the amount of students who are prepared for college-level mathematics encompasses a myriad of issues such as teaching standards, curriculum, assessment, learning, and professionalism.

Institutions that utilize differentiated teaching and learning strategies have been found to improve the success rate of students in developmental mathematics (Boylan, 2002; Epper & Baker, 2009). According to Bonham and Boylan (2011), student success in developmental math has been linked to the application and use of research-based instructional practices and new approaches to teaching math content.

As opposed to students being lectured in a traditional manner, institutions have utilized a self-paced delivery option through a computer program referred to as ALEKS. In addition to the emphasis on mastery from the program, colleges have adopted Supplemental Instruction and tutoring for developmental math students to ensure better learning outcomes. Foothills College in California evolved their developmental math program into a system called Math My Way by implementing the aforementioned efforts and have observed a 20% higher success rate for their students (Bonham & Boylan 2011). The clear positive of such an approach is that students are learning mathematical concepts by being provided ample opportunity to apply course material in class, rather than on their own time. The challenge to this area of research is that many of the conclusions reached in research related to the effectiveness of developmental education are inconclusive or rely solely on subjective qualitative questionnaires or evaluations, rather than quantitative data and statistical analysis (Jacoby, 2006; Merisotis & Phipps, 2000).

Lavin, Alba, and Silberstein (1981) found through a five-year analysis that students who successfully completed their remediation were more likely to persist to graduation than similarly prepared, low-skilled, non-remedial students. Similar to Lavin et al. (1981), Bettinger and Long (2004) found that students who were successful in developmental mathematics persisted to graduation more so than academically similar non-remedial students. Additionally, Attewell et al. (2006) found that students who successfully completed developmental requirements only took two to three additional months to reach graduation. However, students that enrolled in developmental

mathematics courses at a four-year institution had a five percent lower chance of reaching graduation than those who had no remedial math obligations, and for students who enrolled in two or more developmental mathematics courses at a two-year college had a three percent lower likelihood of graduating (Attewell et al., 2006).

While this seems insignificant, the data evaluated by Attewell et al. (2006) also showed that only thirty percent of the students enrolled in remedial math successfully passed the course the first time it was attempted. Even after controlling for academic skills and background, “. . . the effect of remedial math courses was ambiguous . . .” (Attewell et al., 2006, p. 916). This finding could serve as an explanation for Bettinger & Long (2004) who found that students who were placed in developmental mathematics were more likely to transfer to a community college or drop out as compared to similarly prepared, low-skilled, non-remedial students. Yet, Pruett et al. (2015) found through a regression analysis that “. . . the odds of success in being retained were 23% higher for students who took a developmental mathematics course compared to students who did not take such a course . . .” (pp. 36-37). This finding aligned with that of Bettinger et al. (2005) who suggested that math remediation could improve student outcomes.

More recently, Jenkins and Cho (2012) found that remediation decreased degree completion, or extended the time that it took for a student to complete a degree. Dadger (2012) concluded similar results that students who were enrolled in the lowest level of developmental math would have fared better if they were able to skip developmental courses altogether. In contrast, Martorell and McFarlin (2011) conducted a study on Texas students who were placed into developmental courses and found that the

developmental courses had little effect on the student's number of attempted hours, degree attainment, or labor market earnings for those that scored near the test-score cut off.

What is evident in the research debate is that the effects of remedial education are highly subjective and appear to be linked to characteristics such as state, institution and student background or academic preparedness (Bettinger et al., 2013). However, Polk-Conley and Squires (2012) challenged higher education faculty and administration on the view that the effectiveness of developmental education should be evaluated by the success of the student in the subsequent college-level courses, as many students drop out before ever reaching the college-level math requirement. In considering the effectiveness of developmental math, the instructors of these courses should be evaluated as a variable in the formula to student success.

Faculty of Developmental Mathematics

Traditionally, developmental courses have a higher rate of employing adjunct instructors, as well as having larger class sizes (Bettinger et al., 2013). In most institutions, part-time faculty members are marginalized, as they tend to have no voice in curriculum development of the courses that they are assigned to teach (Wyles, 1998). Boylan (2002) and Boylan and Saxon (1998) suggested that the most successful developmental education programs utilize a higher percentage of full-time faculty.

Jacoby (2006) found that the overuse of part-time faculty in developmental education has a negative effect on student retention. Burgess and Samuels (1999) conducted a study relating the impact of full-time or part-time instructor status on

developmental math students' academic success and retention in sequential courses. The researchers found that students who were enrolled in a developmental introductory algebra course with a part-time instructor and then were enrolled in a developmental intermediate algebra course with a full-time instructor were significantly less likely to earn a "C" or better than any other instructor combination (Burgess & Samuels, 1999). However, the student population that had the first and second developmental math course with a part-time instructor for each course fared better than expected. These results support a common notion that part-time instructors are ". . . more lenient, less demanding, and grade higher than full-time instructors . . ." (Burgess & Samuels, 1999, p. 496).

Contrastingly, Penny and White (1998) employed a regression analysis in determining if developmental mathematics instructor attributes indirectly affected a student's performance in the course. Through their analysis, the results indicated that there was a direct relationship between the instructor's employment status and gender and student performance in developmental mathematics. The results showed that students who had a full-time instructor in developmental mathematics performed better in their college level mathematics course than students who had a part-time instructor for developmental math. Interestingly, Gross (1981) posed the ideology that faculty at senior research institutions have negative attitudes about remediation and the students, and are often unprepared to teach the developmental course. In more recent research, many faculty instructors have been found to question why students who need developmental

intervention are even allowed to enroll in higher education, or why these courses are being taught (Bonham & Boylan, 2011).

The American Math Association for Two Year Colleges (2006) standard on professionalism suggested that developmental mathematics instructors need specialized training in teaching preparation, technical mathematics, and possess an intensive math background. Boylan (2002) found that faculty training and professional development were prominent factors in the most successful developmental programs. However, many educators who are highly qualified in the discipline of mathematics lack the formal training in order to appropriately teach developmental education (Bonham & Boylan, 2011).

Professional development for remedial mathematics teaching provides instructors the opportunity to evaluate how math pedagogy continually evolves to identify how curriculum should be reviewed and revised (Bonham & Boylan, 2011). Faculty of developmental math need to be confident and cognizant through professional development on how to make decisions regarding the best methods to use in the application of course material, and how to provide appropriate and responsive feedback to students, both of which should align with the goals of the National Association for Developmental Education (Kinney, 2001; Schnee 2014). Through the utilization of a multimodality approach, such as integrated group work, developing students based on their learning style, and providing frequent opportunities to develop math skills, instructors and students can plan for success in developmental math.

Research by Zavarella and Ignash (2009) and Ashby et al. (2011) has shown that the learning environment created by the instructor affects developmental students' completion rates. The findings suggest that institutions should be cognizant in providing environments that support success of students in developmental courses, as enrolling in developmental coursework can be frustrating for a student. Sierpiska, Bobos, and Knipping (2008) found that the real frustration of students came from a lack of interest from the faculty teaching the course, a lack of understanding from their instructors, and a lack of support provided to the student from the college.

Faculty of developmental math can play a large role in a student's success in the course, but Boylan (2011) stressed the importance that it cannot be left to the math department alone to assist these students. A collaborative effort between policy makers, developmental mathematics instructors and the institution needs to be developed in evaluating “. . . how developmental math courses are structured, taught, and delivered . . .”, especially in consideration to the characteristics of the students within the classroom and how those demographics might affect student success (Boatman & Long, 2010, p. 6).

Characteristics of Students in Developmental Education

Students in developmental education can range from a myriad of backgrounds and demographics. However, there are certain demographics that tend to be prevalent among those students that are enrolled in developmental courses. Most students who are in developmental coursework are recent high school graduates who are lacking the academic preparation needed to be mainstreamed into college courses. Underprepared students seem to confront more problems while adjusting to the new college lifestyle.

As a student struggles in the classroom, it can ultimately lead to greater frustration and low self-esteem, as well as higher dropout rates (Bettinger et al., 2013). Research has identified that the students who are most commonly enrolled in developmental programs for math are first-generation, low-income and minority students (Bailey, Jenkins, & Leinbach, 2005; Bettinger et al., 2013; Epper & Baker, 2009; Polk-Conley & Squires, 2012). Additionally, higher education professionals who support college remediation highlight the fact that students who are of color, from less affluent families, and students who speak English as a second language are highly overrepresented in developmental education (Attewell et al., 2006). Penny and White (2001) conducted a regression analysis to determine how student attributes might affect a student's performance in developmental mathematics. The analysis revealed that there was a direct relationship between ethnicity, age, enrollment status and a student's performance in the course.

While remedial courses have been evaluated and tried with various academic interventions, it is possible that student demographics have varying effects on the successful completion of developmental courses. It is important to fully understand how these variables may relate to a student's ability to be successful in developmental math in relation to the instructor's employment classification. Thus, first-generation status, race, and gender were included as demographic variables in the present study.

First-generation students.

As American higher education has become more accessible, an increase in enrollment among the first-generation student population has developed. Reports show

that a decrease in family size of the American non-first generation population has occurred, which suggests why an influx in the percentage of first-generation students make up a large percentage of higher education enrollees (Davis, 2010). With evidence pointing to the increased enrollment of first-generation students an importance should be placed in how to develop first-generation students towards academic success.

Defining the first-generation student has proven to equip practitioners with a broadly accepted definition. First-generation students are viewed as students whose parents who do not hold a baccalaureate degree (Ward, Siegel, & Davenport, 2012, p. 3). First-generation students tend to be minority students whose families have an unsure stance on the value of obtaining a higher education (Wildhagen, 2015). Research has shown that students who are the first in their family to attend college are inclined to struggle the most with acclimating successfully to the college culture (Blackwell & Pinder, 2014; Wolcott & Gore-Mann, 2009). The experience of a first-generation student at a four-year institution can be the most intense (Davis, 2010). An institution's size and organizational procedures tend to allow for students to fall through the cracks in creating more challenges for first-generation students to seek help (Davis, 2010).

Compared to non-first generation students, first-generation students are more likely to have received inadequate academic preparation, to have experienced difficulty obtaining information about postsecondary opportunities, to have come from low socio-economic backgrounds, and to have missed out on peer tutoring, resulting in lower academic skills social skills, and self esteem; all of which are vital to student success (Backwell & Pinder, 2014; Chen, 2005; Petty, 2014). Often, first generation students

believe themselves to be outsiders who do not really fit in the world of academia; which then becomes a compound concern relating to student motivation (McKay & Estrella, 2008).

In identifying first-generation students with academic motivational concerns, retention becomes an area of focus for institutions of higher education. In several studies the researchers discovered that if first-generation students can successfully navigate the academic and social world of college, they have higher retention rates than non-first generation students and better chances for matriculating from college (Braxton, Jones, Hirschy, & Hartley, 2008; Umbach, Palmer, Kuh, & Hannah, 2006; Woosley & Shepler, 2011).

First-generation students who achieved success had family members who supported and encouraged the students in their collegiate endeavors (Blackwell & Pinder, 2014; Martin, Harrison, & Bukstein, 2010). Blackwell and Pinder (2014) interviewed three first-generation college graduates who supported the researcher's' assertion that the family environment “. . . can influence self-efficacy through parental support and encouragement . . .” (p. 47). First-generation students have been shown to benefit from the involvement of collegiate faculty and administration, as well. Woosley and Shepler (2011) concluded from their study that faculty and collegiate professionals could improve the experience of first-generation students by “. . . working to create and foster a campus environment that enables students to feel accepted and promotes academic performance . . .” (p. 711).

A primary challenge of the rising math requirements, as found in the research of Bailey et al. (2005) and Epper and Baker (2009) is that “. . . the majority of students who test into remedial math coursework are disproportionately minority and disproportionately first-generation, two characteristics of at-risk students . . .” (p. 3). According to Chen (2005), forty percent of first-generation college students enrolled in developmental math, as compared to only sixteen percent of non-first generation students. Parental education attainment has been shown to affect a college student’s attrition rate (Ishitani, 2006).

First-generation students are more likely to enroll in remediation classes, enroll in classes multiple times, take longer to complete their degrees, depart and never return to the postsecondary institution, and not achieve the aspirations that they had as pre-college students (Choy, Horn, Nunez, & Chen, 2000; Ishitani, 2006; McCarron & Inkelas, 2006). Additional research shows that first-generation students typically do not complete higher education at the same rate as non-first generation students (Chen & Carroll, 2005; Pike & Kuh, 2005).

Early research found that parental education of a student enrolled in developmental mathematics did not have a statistically significant relationship with student retention (Umoh et al., 1994). However, Pruet et al. (2015) utilized a logistic regression model to determine what factors influenced the retention of developmental education students. In their research they found the parent’s education level to be statistically significant, as the likelihood of success in being retained were 11.4% higher for students whose parents had some college education as opposed to the students whose

parents had no college degree (Pruett et al., 2015, p. 39). The same findings were prevalent in similar research conducted by Pascarella and Terrenzini (2005) that students whose parents had some college experience were twice as likely to earn a bachelor's degree compared to students who were considered first-generation.

Most research on first-generation students tends to focus on the student population as a group rather than focusing on ethnic minorities within the group (Dennis, Phinney, & Chuateco, 2005). However, it is suggested that students are considered within their race, gender, or social class as these variables can affect their ability to engage and learn (Ward et al., 2012).

Race.

There are higher education professionals who are in favor of adopting policies that deny admission to students who are need of developmental intervention. However, doing so would impact mostly minority students (Attewell et al., 2006). Research has shown that developmental education students who choose to withdraw from college do so due to the presence of a hostile racial environment in the classroom (Pascarella & Terrenzini, 1991; Umoh et al., 1994).

Penny & White (1998) found through a regression analysis that African-American and Hispanic ethnic groups were at a higher risk of poor academic performance in developmental mathematics courses. The same was true for these ethnic groups in relation to their success in a college-level math course after completing the developmental math course. Other ethnicities, such as Asian and Native-American groups had no significant effect on a student's performance (Penny & White, 1998).

Attewell et al. (2006) found through a regression analysis that there was a statistical significance of African-American students versus White students when it came to enrolling in developmental education. Regardless of having the same academic preparation and background, African-American students had a higher enrollment in developmental courses than White students by eleven percent (Attewell et al., 2006). Additionally, Bettinger et al. (2013) found that the sequencing success of students who place into developmental mathematics have been identified as extremely low for men and African-American students.

The Hispanic population has been identified as highly overrepresented in developmental courses due to their low representation in college preparatory courses at the high school level (Brickman, Alfaro, Weimer, & Watt, 2013; Chen & Carroll, 2005; Pike & Kuh, 2005; Solorzano & Ornelas, 2004). Portions of students enrolled in developmental education were not born in the United States or speak English as a second language (Bettinger et al., 2013). Additionally, Villalpando (2010) estimated that only nine out of one hundred Hispanic students complete a post-secondary degree. However, in a study conducted by Watt, Huerta, and Alkan (2011), Hispanic students who successfully completed required remediation showed to be on track to graduate in a timely manner at a higher rate than Hispanic freshmen who were not required to go through remediation. This result has been found to be true throughout more research (Brickman et al., 2013). Additional research has found that an effective strategy in developing mathematical skills and confidence for minority students is to carefully

design a writing assignment in order to foster student learning and engagement with the mathematical concepts (Loud, 1999; Meier & Rishel, 1998; Pugalee, 1997).

Gender.

In 1994, Umoh et al. conducted a quantitative study which found that gender did not have a significant effect on student retention in developmental mathematics, which aligned with a similar study conducted by Bean and Metzner (1987). In alignment with these results, Penny & White (1998) found that gender also had no significant effect on student performance in a developmental mathematics course, as well as the subsequent college algebra course. Yet, in previous research conducted on gender and student performance, Kagan and Budros (1992) it was found that males tend to perform better than females in developmental mathematics. Contrastingly, Long and Calcagno (2011) found that women had a more positive effect from placing into developmental courses than men. Bailey, Jeong, and Cho (2010) found support that gender is a related variable to a student's progression in developmental education.

In a study conducted by Waycaster (2010), the participation rates by gender in the developmental mathematics class observed was determined by the gender makeup of the class. For example, if the class was predominantly made up of female students then the majority of participation came from female students and vice-versa. According to previous research conducted, this pattern aligned with what is already known about the gender makeup of student participation in developmental mathematics (Waycaster, 2010). From the results of this study, developmental educators need to be cognizant of

the dominant gender of the course and the dynamic role that gender plays in engaging the minority gender in class participation.

Social Cognitive Theory

Social cognitive theory maintains that a student's beliefs about the value of course material and learning experience, and the enjoyment that the student receives from the course in order to motivate them towards engagement with the content plays a vital role in a student's ability to persist in spite of failures (Bandura, 1997). Researchers have found a correlation between a student's attitude towards math and the student's achievement in math (De Corte, Verschaffel, & Depaepe, 2008; Ma & Xu, 2004; Muis, 2004). Research has also identified the impact of other affective factors outside of attitudinal factors that relate to student success in developmental mathematics. Some of these factors are low self-efficacy, one's confidence related to math, test anxiety, and math anxiety (Bates, 2007; Bonham, 2008; Hall & Ponton, 2005; Higbee & Thomas, 1999; Rodriguez, 2002; Tobias, 1993). Brickman et al. (2013) related a student's ability to be successful in developmental math and overcoming math anxiety to social cognitive theory in helping a student set clear pathways on how developmental math related to their goal achievement.

Boylan (2011) suggested that math anxiety could decrease test performance in which students are then placed into remediation rather than being enrolled in a credit-bearing course. Math anxiety began as a new concept in the early 1970's when researchers Richardson and Suinn (1973) coined the term "matheophobia." This term

represented student's unwillingness to learn math and therefore resulted in a lack of engagement with mathematics content.

The research of math anxiety has evolved to identify an inclusive definition as the fear of going to class, completing homework, or having an emotional worrisome response to math (Boylan, 2011). Math anxiety can prohibit a student from testing at the required level even though the student may know the material (Nolting, 2008). Additionally, math anxiety and math phobia also play a role in a student's ability to successfully complete a developmental course. Due to fear of failure, students often avoid the math subject as long as they can, only to prolong their ability to enroll in a credit bearing math course.

Professionals who work with students in developmental math can help reduce a student's math anxiety by firstly identifying that it is a real obstacle that students need support in overcoming (Shields, 2007). As research continues regarding math anxiety, researchers found that instructors can utilize different techniques in assisting students to overcome their fear of math; such as self-awareness, relaxation methods, and enhanced study skills (Tobias & Weissbrod, 1980). It has even been mentioned that the integration of counselors as guest speakers in a developmental math course could help students overcome math anxiety (Boylan, 2011). The influence of affective factors can greatly impact a student's ability to succeed in developmental math. Faculty, support staff, and even students need to be cognizant of these barriers in order to better develop and employ appropriate strategies to achieve academic success. Approaches to doing so should strive to build student self-confidence, maximize student learning, and work towards alleviating math anxiety. By creating a supportive community environment in developing

camaraderie, a student's belief about the course and its content can become positive and enjoyable, in which performance levels increase (Barkley et al., 2005; Davidson & Kroll, 1991). The welcoming and safe environment allows students to feel connected, safe, and comfortable in expressing questions or misunderstandings.

Summary

In considering the present literature on developmental education, there are conflicting research studies on the effectiveness of developmental mathematics, the role of the faculty within the classroom, and how student characteristics affect a student's ability to be successful within a developmental math course. The research is underpinned through the social cognitive theory in order to pose an additional foundation in holistically understanding and determining a reason for poor success rates in developmental mathematics. The present study seeks to add clarity to the current inconsistent literature in identifying how an instructor's employment classification, student gender, race, and first-generation status in predicting a student's academic success in developmental mathematics at one regionally comprehensive research institution in Texas between fall 2013 and spring 2017.

CHAPTER III

Methodology

Introduction

Texas college-readiness standards are set to increase once again, yet the developmental math pass rates across the state of Texas are at an all-time low with only 20% of remedial students completing developmental requirements successfully and moving forward to earn a bachelor's degree within six years (Higher Education Performance Review, 2007). Research in evaluating how a developmental math instructor's employment classification paired with student attributes might influence a student's academic success in the course has been largely inconsistent. The problem addressed in this study was to determine how the employment of lower-level developmental math instructors might influence a student's ability to pass the course, in addressing the issue that many institutions employ part-time, under qualified faculty to manage developmental math courses and the negative implications this might have on student outcomes (Bettinger et al., 2013).

Purpose

The purpose of this binary logistic regression model research was to determine what type of predictive power exists between an instructor's employment classification,

student gender, student race, and first-generation status on a student's academic success in developmental mathematics, as measured by final semester grades at a regionally comprehensive state university in Texas between fall 2013 and spring 2017.

Research Questions

The following research questions were addressed:

1. Does an instructor's employment classification predict a student's academic success (receive a grade of C or better) in developmental mathematics?
2. Does an instructor's employment classification and a student's gender predict a student's academic success (receive a grade of C or better) in developmental mathematics?
3. Does an instructor's employment classification and a student's race predict a student's academic success (receive a grade of C or better) in developmental mathematics?
4. Does an instructor's employment classification and a student's first generation status predict a student's academic success (receive a grade of C or better) in developmental mathematics?

Research hypotheses.

In considering previous literature and the purpose statement of this research as a director, the following research and null hypotheses were tested in relationship to the research questions under consideration.

1. H₁: An instructor's employment classification does predict a student's academic success (receive a grade of C or better) in developmental mathematics.

2. H₂: An instructor's employment classification and a student's gender predicts a student's academic success (receive a grade of C or better) in developmental mathematics.
3. H₃: An instructor's employment classification and a student's race predicts a student's academic success (receive a grade of C or better) in developmental mathematics.
4. H₄: An instructor's employment classification and a student's first-generation status predicts a student's academic success (receive a grade of C or better) in developmental mathematics.

Null hypotheses.

1. H₀₁: An instructor's employment classification does not predict a student's academic success (receive a grade of C or better) in developmental mathematics.
2. H₀₂: An instructor's employment classification and a student's gender do not predict a student's academic success (receive a grade of C or better) in developmental mathematics.
3. H₀₃: An instructor's employment classification and a student's race do not predict a student's academic success (receive a grade of C or better) in developmental mathematics.
4. H₀₄: An instructor's employment classification and a student's first-generation status do not predict a student's academic success (receive a grade of C or better) in developmental mathematics.

Research Design

This study used a binary logistic regression analyses to explore the probability that the predictor variables selected (instructor employment classification, student race, student gender, first-generation status) will impact the dependent variables (pass or fail in developmental mathematics) under study at one public Texas institution of higher education between fall 2013 and spring 2017. According to Salkind (2010), “. . . binary logistic regression assumes an interest in prediction, regardless of whether causality is implied . . .” (p. 730). Rather than look for directional relationships or power of relationships, as done so with simple linear and multilinear modeling, binary logistic regression looks to explain the predictive power of independent variables on a dependent outcome. Additionally, binary logistic regression is used when the dependent variable is a true or forced dichotomy and the independent variables can be of any type (Garson, 2014).

This research study explored a dichotomous binary dependent variable, pass or fail, which exists in relationship to predictor variables related to students’ enrollment in developmental math. Additionally, for binary responses, traditional linear regression models are ineffective at accurately modeling the binary response. Therefore, binary logistic regression analysis is ideally suited to describe the relationships between the observed variables.

Sample

This study explored the relationships between an instructor level predictor variable and student achievement in developmental math as the dependent variable

outcome. Therefore, there are two primary populations and samples under study. The first population of this study was all students enrolled in developmental math 099 for the first time at one Texas public institution of higher education during the period between fall 2013 and spring 2017. This sample population was the total for this group, which included 1932 unique student observations. For the purpose of this study, the sampling for this population was purposive due to the fact that the nature of the research questions necessitated that only members of a specific group were included in the sample (Salkind, 2010).

The second population under study were the instructors who taught developmental math 099 to the student population enrolled in the course during the period between fall 2013 and spring 2017 at the Texas public institution of higher education being studied. For the purposes of this study, the sampling of instructors was purposive due to the fact that the research questions require that only the instructors that met the requirements of teaching developmental math 099 during the selected time frame were included in this study.

Data Collection

Data for this study was collected through a request made to the Texas regional comprehensive four-year university's General Counsel and Family Educational Rights and Privacy Act (FERPA) committee to receive a dataset for all students enrolled in developmental math 099 at the institution from fall 2013 to spring 2017 (see Appendix A). An informed consent was sent to the General Counsel to inform the university of the purpose of this research and gain permission from the university to allow their

participation in this study (see Appendix B). The Information Technology Services Office then sent the researcher a comma-separated values (.csv) file containing all of the requested data in one unedited dataset.

The requested data for this research contained the following data points: the semester code of each math 099 course during the time frame selected; the student's unique identification number to ensure duplication enrollment is removed; the assigned instructors' and their employment classification; each student's earned letter grade in the course; each student's race; each student's gender; and each student's first-generation status. All of this information was provided by the institution's Information Technology Services Office and pulled from the university's data management Banner Information System.

Data Analysis

The data provided by the Information Technology Services Office included all relevant points for this research. The data was downloaded in general format without specific coding, and was in non-numerical format. However, in order to run the logistic regressions, the data was coded numerically in order to allow for statistical testing.

For the instructor level variable, the three possible outcomes were coded as: TA=1; ADJUNCT=2; and LECTURER=3. The variables were given a hierarchical characteristic to denote the increasing level of employment from the lowest level of TA to the highest level of LECTURER. For the race variable, the five possible outcomes were coded as: White=1; Black or African-American=2; Hispanic=3; Asian=4; and two or more=5. Gender was coded as female=0 and male=1. First-generation status was

coded as no=0 and yes=1. Finally, all grades labeled as RC, RB, and RA were coded as 1 for passing, and RD, RF, and RQF were coded as 0 for not passing.

Once the data was coded into a numerical format, it was exported into a dataset that was able to be imported into statistical software for analysis. The researcher used the Statistical Package for the Social Sciences (SPSS) to run binary logistic regression analyses on the data for each independent variable under study. Additionally, SPSS was used to create descriptive statistics of the data, and Microsoft Excel was used to create additional descriptive statistics and any data visualizations and charts that were presented in the findings and discussions.

The researcher was most interested in finding the odds ratios, listed as Exp(B) in the SPSS output, to determine how the odds change for the dependent variable with a one unit increase in each predictor variable while holding all other variables constant. The researcher also looked for statistical significance in the odds ratio, or a p-value of 0.05 or below, to represent that the odds ratio finding is significant at a 95% confidence interval rate. Furthermore, the researcher determined the fit of the model in two ways. First the researcher was interested in the -2 Log-likelihood indicator to describe how much unexplained information there is after the model has been fitted, as a large -2 Log-likelihood indicates a poorly fitted statistical model. Secondly, the researcher ran the Hosmer and Lemeshow Test, which is an output that gives the researcher an idea of how good the logistic model is at prediction. As Hosmer, Lemeshow, and Sturdivant (2013) described, “. . .after estimating the coefficients, our first look at the fitted model commonly concerns an assessment of the significance of the variables in the model . . .”

(p. 11). This usually involves formulation and testing of statistical hypotheses to determine whether the independent variables in the model are significantly related to the outcome variable. Unlike previous significance levels, in the Hosmer, Lemeshow and Studivant (2013) Test the researcher wanted the p-value to be higher than 0.05 because that indicates that the model is significant. In this test, if there is a p-value below 0.05 then it means that the model is not a particularly good fit for the data set. Essentially, this test answered the question of whether the probabilities produced by the model accurately reflect the true outcome experience in the data.

Summary

In traditional simple and multi-linear models, the probabilities are inherently unbound (Allison, 2012). By attempting to place a linear regression line onto a binary dependent variable response, a researcher would not be able to extrapolate any meaning as the linear line tries to find the line of best fit. Yet, binary responses fall between each point in the data bound by 0 and 1 in which a binary logistic regression analysis should be utilized to appropriately graph the response variables. Binary logistic regression seeks to model the probability of an event occurring depending on the values of the independent variables, which can be categorical or numerical. The regression model attempts to estimate the probability that the event does not occur. It also tries to predict the effect of a series of variables on a binary response. Additionally, binary logistic regression classifies the observations by estimating the probability that an observation falls within a particular category (Foltz, 2015). Finally, binary logistic regression is used

when the dependent variable is a true or forced dichotomy and can only have one mutually exclusive outcome, pass or fail in the case of this research study (Garson, 2014).

CHAPTER IV

Findings

Introduction

The purpose of the research was to determine what type of predictive power existed between an instructor's employment classification, student gender, student race, and first-generation status on a student's academic success in their first attempt in developmental mathematics, as measured by final semester grades at a regionally comprehensive state university in Texas between fall 2013 and spring 2017. By focusing on instructor employment classification and its relationship to student outcomes in developmental math, the findings below provide context for university administrators to begin discussing what factors affect a student's success in developmental math, specifically related to the instructor's employment classification, student gender, race, and first-generation status.

Data were collected from the Texas regional institution under study by approval from the university's General Counsel and Family Educational Rights and Privacy Act (FERPA) committee. The data set was then provided to the researcher from the institution's Information Technology Services Office, as it was collected from the university's data management Banner Information System. This chapter begins with a

summary of the descriptive statistics for the data collected, followed by an analysis of the binary logistic regressions used to answer each of the four research questions.

The Statistical Package for the Social Sciences (SPSS), version 24, was used to run the binary logistic regression statistics and to analyze the data in order to answer the four research questions. Additional descriptive statistics were developed using Microsoft Excel.

Descriptive Statistics

Descriptive statistics for total number of students enrolled in MTH 099 for the first time broken down by instructor employment classification for fall 2013 to spring 2017 can be found in Table 1 below. The total number of students in this study was 1932, 70.8% of which were taught by Graduate Teaching Assistants. In addition to that, 10.1% of students enrolled in MTH 099 were taught by Adjunct Instructors and 18.9% were taught by Lecturers. In looking at the number of students taught by instructor level, the vast majority of students during the 2013-2017 timeframe were taught by Graduate Teaching Assistants (1368), then Lecturers (367), and then Adjunct Instructors (197).

Table 1

Number of Students Taught by Instructor Level

Variable Name	Students Taught
Graduate Teaching Assistant	1368
Adjunct Instructor	197
Lecturer	367
<i>N</i>	1932

Table 2 shows the descriptive statistics for student grade distribution based on instructor level, as well as the percentage number of students who passed the course, meaning the student received a grade of RC (remedial C average), RB (remedial B average), or RA (remedial A average). Students who received a grade of RD (remedial D average), RF (remedial F average), RQF (remedial Quit Failing average), or RWH (remedial incomplete average) are identified as not passing MTH 099. In looking at Table 2, it is apparent that Graduate Teaching Assistants passed fewer students than Lecturers or Adjunct Instructors. 934 students did not pass MTH 099 with Graduate Teaching Assistants, while only 118 did not pass with Adjunct Instructors, and 243 did not pass with Lecturers. In looking at the 424 students that earned an RQF average, 302 of those students were taught by Graduate Teaching Assistants; meaning 71.2% of all students who quit attending the course and earned an RQF were enrolled with Graduate Teaching Assistants.

Table 2

Grade Breakdown by Instructor Level

Variable Name	Grade Earned							%PASS
	RA	RB	RC	RD	RF	RQF	RWH	
Graduate Teaching Assistant	36	109	289	158	473	302	1	31.73%
Adjunct Instructor	10	31	38	21	66	31	0	40.10%
Lecturer	11	40	73	41	109	91	2	33.79%
<i>N</i>	1932							

Table 3 provides descriptive statistics on student outcomes in MTH 099 broken down by race. Students categorized as White successfully completed MTH 099 on their

first attempts at the highest rate of all racial groups in this study with a 51.4% pass rate. Black students successfully passed the course 48.02% of their first attempt, and Hispanic students passed the course 33.06% of the time on their first attempt. Students who identified as two or more races fared far worse than any other racial population in this study, as only 3.74% of this population passed MTH 099 in their first attempt.

Table 3

Grade Breakdown by Race

Variable Name	Grade Earned							%PASS
	RA	RB	RC	RD	RF	RQF	RWH	
Black or African American	12	43	139	41	85	84	0	48.02%
Hispanic	10	38	73	44	125	76	0	33.06%
Two or More	1	6	15	96	302	167	2	3.74%
White	31	88	157	38	125	97	1	51.40%
<i>N</i>	1932							

In looking at the descriptive statistics of grade breakdown by Instructor Level and race on student outcomes in MTH 099 in Table 4, African American students highest pass rate is with Adjunct Instructors (52.5%) and their lowest pass rate is with Lecturers (47.13%). Hispanic students highest pass rate is with Adjunct Instructors (46.67%) and their lowest pass rate is with Lecturers (29.31%). Students who identify as having Two or more races highest pass rate is with Adjunct Instructors (5%) and their lowest pass rate is with Graduate Teaching Assistants (3.49%). Finally, White students highest pass rate is with Adjunct Instructors (58.73%) and their lowest pass rate is with Lecturers (48.7%). The overall theme of this descriptive data is that all students in Table 4 show to have a

higher pass rate with Adjunct Instructors than any other instructor employment classification.

Table 4

Grade Breakdown by Instructor Level and Race

	Graduate Assistant			Adjunct			Lecturer		
	Pass	Fail	% Pass	Pass	Fail	% Pass	Pass	Fail	% Pass
Black or African American	132	145	47.65%	21	19	52.50%	41	46	47.13%
Hispanic	90	188	32.37%	14	16	46.67%	17	41	29.31%
Two or More	15	415	3.49%	3	57	5.00%	4	93	4.12%
White	183	175	51.12%	37	26	58.73%	56	59	48.70%

Table 5 provides a breakdown of grades received by gender for students enrolled in MTH 099. Female students are observed to have a higher pass rate than male students, as 37.62% of females passed MTH 099 compared to only 23.77% of male students.

Table 5

Grade Breakdown by Gender

Variable Name	Grade Earned							%PASS
	RA	RB	RC	RD	RF	RQF	RWH	
Male	11	31	112	72	218	203	1	23.77%
Female	46	149	288	148	430	221	2	37.62%
<i>N</i>	1932							

In looking at the descriptive statistics of grade breakdown by Instructor Level and gender on student outcomes in MTH 099 in Table 6, it is shown that males have a higher

pass rate with Lecturers (27.48%) and females have a higher pass rate with Adjunct Instructors (50%). Both genders show to have a lower pass rate when enrolled in MTH 099 in their first attempt with a Graduate Teaching Assistant.

Table 6

Grade Breakdown by Instructor Level and Gender

	Graduate Assistant			Adjunct			Lecturer		
	Pass	Fail	% Pass	Pass	Fail	% Pass	Pass	Fail	% Pass
Male	101	342	22.80%	17	56	23.29%	36	95	27.48%
Female	333	591	36.04%	62	62	50.00%	88	146	37.61%

The descriptive statistics in Table 7 provides a grade breakdown for first-generation students compared to non-first generation students. First-generation students a 34.85% pass rate in MTH 099 compared to non-first generation students who only passed MTH 099 30.1% of the time on their first attempt in the course.

Table 7

Grade Breakdown by First Generation Status

Variable Name	Grade Earned							%PASS
	RA	RB	RC	RD	RF	RQF	RWH	
First Generation	40	118	249	135	376	249	1	34.85%
Non-First Generation	17	62	151	85	272	175	2	30.10%
<i>N</i>	1932							

In Table 8, the descriptive statistics provide a grade breakdown by Instructor Level and First Generation status on student outcomes in MTH 099. Based on these descriptive statistics, first generation students and non-first generation students have a

higher percentage pass rate with Adjunct Instructors, while the lowest pass rate for both student categories is with Graduate Teaching Assistants.

Table 8

Grade Breakdown by Instructor Level and First Generation

	Graduate Assistant			Adjunct			Lecturer		
	Pass	Fail	% Pass	Pass	Fail	% Pass	Pass	Fail	% Pass
First Generation	285	570	33.33%	41	48	46.07%	81	142	36.32%
Non-First Generation	149	363	29.10%	38	70	35.19%	43	99	30.28%

The findings of a simple linear regression analysis of all the general variables under study begins by showing that there are relationships between the variables in the model that deserve further study, as the linear model is significant ($\text{Prob}>F = 0.0000$). A student's level of success with an adjunct instructor compared to a graduate teaching assistant has a positive, significant coefficient, as does the relationship between race. The gender variable shows a negative relationship in student outcomes and is statistically significant. In the overall linear regression model first generation status and lecturer instructor status do not appear to be significantly correlated with overall student success in MTH 099. The following logistic regressions will examine the probability outcomes of each of the variables under study in greater detail and the marginal effects of the logistic regressions will be analyzed to understand the relationships between changes in each variable and changes to student pass/fail outcomes in MTH 099.

Table 9

Linear Regression for Student's Academic Success and Instructor Level, Race, Gender and First Generation Status

Variable Name	Student's Academic Success				
	Coef.	Std. Err	P> t	[95% Conf. Interval]	
Adjunct vs. GA	0.0788	0.0347	0.023	0.0108	0.1468
Lecturer vs. GA	0.0132	0.0266	0.620	-0.0390	0.0653
White	0.2478	0.0233	0.000	0.2021	0.2934
Male	-0.1359	0.0218	0.000	-0.1786	-0.0931
First Generation	0.0166	0.0214	0.437	-0.0253	0.0586
Constant	0.2858	0.0198	0.000	0.2470	0.3246
Prob > F	0.0000				

Results of Research Questions

Research Question 1 – Does an instructor's employment classification predict a student's academic success (receive a grade of C or better) in developmental mathematics?

The findings of the logistic regressions for student academic success and instructor level shown in Tables 10 and 11 below indicate that there is a relationship between an instructor's employment classification and student success in MTH 099. For students enrolled in MTH 099 with Adjunct Instructors instead of Graduate Teaching Assistants, the odds ratio for passing the course was 1.44, a finding that is shown to be statistically significant at the 5 percent level ($P>|z|=0.020$). For students enrolled with Adjunct Instructors instead of Graduate Teaching Assistants, the marginal effects after

the logistic regression indicate that there is a maximum likelihood of an 8.42% greater chance of passing the class. The odds ratio is also positive for students enrolled in MTH 099 with Lecturers instead of Graduate Teaching Assistants but the finding is not statistically significant ($P > |z| = .453$). The odds ratio is negative (0.7622) for students enrolled in MTH 099 with a lecturer instead of an Adjunct Instructor, but that finding is also not significant. Overall, the regression model with these variables is not statistically significant ($\text{Prob} > \chi^2 = 0.065$).

Table 10

Logistic Regression for Student's Academic Success and Instructor Level

Variable Name	Student's Academic Success				
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]	
Adjunct vs. GA	1.4408	0.2256	0.020	1.0601	1.9582
Lecturer vs. GA	1.0982	0.1370	0.453	0.8600	1.4023
Lecturer vs. Adjunct	0.7622	0.1391	0.137	0.5330	1.0900
Prob > chi2	0.0650				

Table 11

Marginal Effects after Logistic Regression for Student's Academic Success and Instructor Level

Variable Name	Student's Academic Success					
	dy/dx	Std. Err	P> z	[95% Conf. Interval]		x
Adjunct vs. GA	0.0842	0.0374	0.024	0.0110	0.1574	0.1020
Lecturer vs. GA	0.0209	0.0281	0.457	-0.0341	0.0759	0.1900
Lecturer vs. Adjunct	-0.0581	0.0378	0.124	-0.1321	0.0159	0.1900

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Research Question 2 – *Does an instructor’s employment classification and a student’s gender predict a student’s academic success (receive a grade of C or better) in developmental mathematics?*

Tables 12 and 13 examine the relationship between male students’ academic success in MTH 099 and instructor level when building a model that only includes male outcomes in the course with each instructor type. The findings of the logistic regression indicate that there is an increased odds ratio for male students who take MTH 099 with an Adjunct Instructor instead of a Graduate Teaching Assistant, and that there is also an increased odds ratio for male students who enroll in MTH 099 with a Lecturer instead of either a Graduate Teaching Assistant or an Adjunct Instructor. However, none of these observations are significant at the 5% level. Overall, the logistic regression model with these variables is not statistically significant (Prob > chi2 = 0.575).

Table 12

Logistic Regression for Male Student’s Academic Success and Instructor Level

Variable Name	Student's Academic Success			
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]
Adjunct vs. GA	1.0279	0.3075	0.927	0.5719 1.8477
Lecturer vs. GA	1.2698	0.2868	0.290	0.8156 1.9770
Lecturer vs. Adjunct	1.2353	0.4187	0.533	0.6357 2.4003
Prob > chi2	0.5746			

Table 13

Marginal Effects after Logistic Regression for Male Student's Academic Success and Instructor Level

Variable Name	Student's Academic Success					x
	dy/dx	Std. Err	P> z	[95% Conf. Interval]		
Adjunct vs. GA	0.0050	0.0547	0.927	-0.1023	0.1123	0.1127
Lecturer vs. GA	0.0448	0.0438	0.306	-0.0410	0.1306	0.2037
Lecturer vs. Adjunct	0.0395	0.0653	0.545	-0.0884	0.1674	0.2037

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Tables 14 and 15 explore the relationship between female students' academic success in MTH 099 and instructor level when building a model that only includes female outcomes in the course with each instructor type. The findings of the logistic regression indicate that there is an increase in the odds ratio for female students who enroll in MTH 099 with an Adjunct Instructor instead of a Graduate Teaching Assistant by a factor of 1.7778. Furthermore, by examining the marginal effects after the logistic regression we can see that the increased odds ratio translates into a maximum likelihood of a 14.02% greater chance that a female student will successfully complete MTH 099 when enrolling with an Adjunct Instructor instead of a Graduate Teaching Assistant. An additional observation is that there is also an increased odds ratio for female students who enroll in MTH 099 with a Lecturer instead of a Graduate Teaching Assistant but that observation is not significant at the 5% level. Furthermore, female students who enroll with Lecturers

instead of Adjunct Instructors have a lower odds ratio, and are overall 11.44% less likely to pass the course, which showed to be statistically significant ($P > |z| = 0.022$). Overall, the findings of this logistic regression model with these variables is statistically significant at the 5% level ($\text{Prob} > \text{chi}^2 = 0.0117$).

Table 14

Logistic Regression for Female Student's Academic Success and Instructor Level

Variable Name	Student's Academic Success				
	Odds Ratio	Std. Err	$P > z $	[95% Conf. Interval]	
Adjunct vs. GA	1.7778	0.3417	0.003	1.2197	2.5912
Lecturer vs. GA	1.0642	0.1609	0.680	0.7913	1.4313
Lecturer vs. Adjunct	0.5986	0.1344	0.022	0.3855	0.9296
Prob > chi2	0.0117				

Table 15

Marginal Effects after Logistic Regression for Female Student's Academic Success and Instructor Level

Variable Name	Student's Academic Success					
	dy/dx	Std. Err	$P > z $	[95% Conf. Interval]		x
Adjunct vs. GA	0.1402	0.0477	0.003	0.0467	0.2337	0.0966
Lecturer vs. GA	0.0147	0.0358	0.682	-0.0555	0.0848	0.1830
Lecturer vs. Adjunct	-0.1144	0.0471	0.015	-0.2068	-0.0221	0.1830

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Research Question 3 – Does an instructor’s employment classification and a student’s race predict a student’s academic success (receive a grade of C or better) in developmental mathematics?

Table 16 shows that there is a relationship between a student’s race and their likelihood for academic success in MTH 099. When using white students as the comparison group, it can be seen that Black, Hispanic and multiracial students all demonstrate lower odds ratios than do white students. While all three groups showed lower odds ratios, two groups, Hispanic students and multiracial students, had significantly lower odds ratios. Hispanic students demonstrated a negative odds ratio of 0.467 which translates into a 12.46% lower chance than White students for passing the course and is statistically significant ($P > |z| = 0.000$). Multiracial students demonstrated an even greater negative odds ratio of 0.0367 which translates into a 44.19% lower chance of passing the course than White students. Overall the logistic model with the racial variables when compared to the White students is significant at the 5% level ($\text{Prob} > \chi^2 = 0.000$)

Table 16

Logistic Regression for Student’s Academic Success and Instructor Level by Race (White Comparison Group)

Variable Name	Student's Academic Success				
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]	
Black	0.8736	0.1151	0.305	0.6747	1.1311
Hispanic	0.4670	0.0657	0.000	0.3545	0.6154

Two or More	0.0367	0.0086	0.000	0.0232	0.0580
Prob > chi2	0.0000				

Table 17

Marginal Effects after Logistic Regression for Student's Academic Success and Instructor Level by Race (White Comparison Group)

Variable Name	Student's Academic Success					x
	dy/dx	Std. Err	P> z	[95% Conf. Interval]		
Black	-0.0247	0.0236	0.296	-0.0709	0.0216	0.2091
Hispanic	-0.1246	0.0205	0.000	-0.1648	-0.0844	0.1894
Two or More	-0.4419	0.0166	0.000	-0.4744	-0.4093	0.3049

(*) dy/dx is for discrete change of dummy variable from 0 to 1

When examining the student outcomes for each racial group based on instructor level and independent of one another instead of against White students in general, the findings indicate how each racial group fares with each instructor level. Table 18 shows no significant differences for White students enrolling in MTH 099 with instructors of various levels. Additionally, the overall model is not significant ($P > \chi^2 = .4218$).

Table 18

Logistic Regression for Student's Academic Success and Instructor Level for White Students

Variable Name	Student's Academic Success			
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]

Adjunct vs. GA	1.3686	0.3789	0.257	0.7955	2.3547
Lecturer vs. GA	0.9128	0.1957	0.671	0.5997	1.3895
Lecturer vs. Adjunct	0.6669	.21122	0.201	0.3585	1.2407
Prob > chi2	0.4218				

Like Table 18 above, Table 19 below indicates that there are no significant differences for Black students enrolling in MTH 099 with instructors of various levels. Also, the overall model for Black student outcomes is not statistically significant (Prob>chi2 = .8336).

Table 19

Logistic Regression for Student's Academic Success and Instructor Level for Black Students

Variable Name	Student's Academic Success			
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]
Adjunct vs. GA	1.2141	0.4112	0.567	0.6251 2.3581
Lecturer vs. GA	0.9791	0.2410	0.932	0.6043 1.5862
Lecturer vs. Adjunct	0.8064	0.3085	0.574	0.3809 1.7069
Prob > chi2	0.8336			

Table 20 below shows that there are no significant differences for Hispanic students enrolling in MTH 099 with instructors of various levels. Also, like both of the above tables discussing White and Black students, this regression model itself is not statistically significant (Prob>chi2 = .2447).

Table 20

Logistic Regression for Student's Academic Success and Instructor Level for Hispanic Students

Variable Name	Student's Academic Success				
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]	
Adjunct vs. GA	1.8278	0.7087	0.120	0.8548	3.9083
Lecturer vs. GA	0.8661	0.2734	0.649	0.4665	1.6080
Lecturer vs. Adjunct	0.4738	0.2208	0.109	0.1901	1.1811
Prob > chi2	0.2447				

Finally, Table 21 below shows that there are no significant differences between instructor level and student success outcomes for multiracial students. Overall, this regression model shows no statistical significance (Prob>chi2 = .843).

Table 21

Logistic Regression for Student's Academic Success and Instructor Level for Students of Two or More Races

Variable Name	Student's Academic Success				
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]	
Adjunct vs. GA	1.4561	0.9436	0.562	0.4089	5.1858
Lecturer vs. GA	1.1649	0.6688	0.790	0.3781	3.5890
Lecturer vs. Adjunct	0.8000	0.6255	0.775	0.1727	3.7039
Prob > chi2	0.8430				

The results of the above regressions indicate that there is a significant difference between the student success outcomes in all MTH 099 sections for non-White students when compared to White students, specifically Hispanic students and multiracial students. However, the within-group effects for racial groups for students enrolling in MTH 099 with instructors of different classifications does not indicate significant differences between instructor levels for any of the racial groups explored in this research.

***Research Question 4** – Does an instructor’s employment classification and a student’s first-generation status predict a student’s academic success (receive a grade of C or better) in developmental mathematics?*

Table 22 indicates that there is a relationship between an instructor’s employment classification and a student’s first-generation status in predicting a student’s academic success in MTH 099. For students enrolled in MTH 099 with Adjunct Instructors instead of Graduate Teaching Assistants, the odds ratio increased by a factor of 1.7113 and is also shown to be statistically significant ($P > |z| = .017$). When looking at the marginal effects for first-generation students, we can see that this odds ratio translates into a 12.84% greater chance that first generation students will successfully pass MTH 099 with an Adjunct Instructor instead of a Graduate Teaching Assistant. The odds ratio is also positive for students enrolled in MTH 099 with Lecturers instead of Graduate Teaching Assistants but the finding is not statistically significant ($P > |z| = .395$). Furthermore, the negative odds ratio for first-generation students enrolled in MTH 099 with a Lecturer instead of an Adjunct Instructor are not significant at the 5% level. Overall, the

regression model with these variables for first generation students is not statistically significant (Prob > chi2 = 0.0531).

Table 22

Logistic Regression for First Generation Student's Academic Success and Instructor Level

Variable Name	Student's Academic Success				
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]	
Adjunct vs. GA	1.7113	0.3845	0.017	1.1017	2.6582
Lecturer vs. GA	1.1428	0.1794	0.395	0.8401	1.5546
Lecturer vs. Adjunct	0.6678	0.1697	0.112	0.4058	1.0991
Prob > chi2	0.0531				

Table 23

Marginal Effects after Logistic Regression for First Generation Student's Academic Success and Instructor Level

Variable Name	Student's Academic Success					
	dy/dx	Std. Err	P> z	[95% Conf. Interval]		x
Adjunct vs. GA	0.1284	0.0555	0.021	0.0197	0.2371	0.0762
Lecturer vs. GA	0.0307	0.0364	0.400	-0.0408	0.1021	0.1909
Lecturer vs. Adjunct	-0.0877	0.0525	0.095	-0.1906	0.0153	0.1909

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Additional Findings

By building a logistic regression model that includes all of the main variables under study, we can conclude the findings by linking the general findings of the overall

logistic model to the original linear model to bookend the more specific logistic findings from the four research questions. The findings of a simple linear regression analysis (Table 9) of all the general variables under study began by showing that there are relationships between the variables in the model that deserve further study, as the linear model is significant ($\text{Prob}>F = 0.0000$). A student's level of success with an adjunct instructor compared to a graduate teaching assistant was shown in that model to have a positive, significant coefficient, as does the relationship for race. In the overall linear regression model, first-generation status and lecturer instructor status did not appear to be significantly correlated with overall student success in MTH 099.

The findings of a complete logistic regression model in Tables 24 and 25 are similar to the findings of the linear model in that they show that there is a significant relationship between instructor level (Adjunct compared to Graduate Teaching Assistant), race, gender, and a student's level of success in MTH 099. Essentially, by adding all of the independent variables to the model we can see relationships between an instructor's employment classification, student's gender and race in predicting a student's academic success in MTH 099. When comparing Graduate Teaching Assistants and Adjunct Instructors, students enrolled in MTH 099 with Adjunct Instructors instead of Graduate Teaching Assistants are predicted to have greater odds ratio by an increased factor of 1.4546 which is shown to be statistically significant ($P>|z|=0.023$). The odds ratio is also positive for students enrolled in MTH 099 with Lecturers instead of Graduate Teaching Assistants but the finding is not statistically significant ($P>|z|=0.619$). The findings of this model predict that male students are less likely to pass MTH 099 than female students

and that White students have higher chances of passing than non-White students.

Overall, the Table 24 regression model with all of the variables included is statistically significant (Prob > chi2 = 0.000).

Table 24

Logistic Regression for Student's Academic Success and Instructor Level, Race, Gender and First Generation Status

Variable Name	Student's Academic Success				
	Odds Ratio	Std. Err	P> z	[95% Conf. Interval]	
Adjunct vs. GA	1.4546	0.2398	0.023	1.0530	2.0094
Lecturer vs. GA	1.0669	0.1391	0.619	0.8264	1.3775
Lecturer vs. Adjunct	0.7333	0.1404	0.106	0.50397	1.0675
White	3.0051	0.3270	0.000	2.4279	3.7195
Male	0.5018	0.0564	0.000	0.4026	0.6255
First generation	1.0829	0.1147	0.452	0.8800	1.3326
Prob > chi2	0.0000				

Table 25

Marginal Effects after Logistic Regression for Student's Academic Success and Instructor Level, Race, Gender and First Generation Status

Variable Name	Student's Academic Success					
	dy/dx	Std. Err	P> z	[95% Conf. Interval]		x
Adjunct vs. GA	0.0851	0.0389	0.029	0.0088	0.1615	0.1020
Lecturer vs. GA	0.0141	0.0287	0.622	-0.0420	0.0703	0.1900
Lecturer vs. Adjunct	-0.0646	0.0383	0.091	-0.1397	.0104	0.1899
White	0.2521	0.0252	0.000	0.2027	0.3016	0.2780
Male	-0.1423	0.0218	0.000	-0.1849	-0.0997	0.3354
First generation	0.0172	0.0228	0.450	-0.0275	0.0619	0.6046

(*) dy/dx is for discrete change of dummy variable from 0 to 1

By examining the marginal effects in Table 25 after the regression analysis we can observe that overall students have an 8.51% greater chance of success in MTH 099 when taking the course with an Adjunct Instructor instead of a Graduate Teaching Assistant, White students overall are 25% more likely than other races to be successful in MTH 099, and men are 14.23% less likely than women to pass MTH 099. All of these observations through this logistic regression are similar to the linear findings from earlier in this chapter.

Finally, it is important to check that the regression model chosen for this research is correctly specified and is the appropriate model to test the data under exploration. The results of the Hosmer and Lemeshow test of statistical significance for this set of regressions indicates that the chosen logistic regression model is a good fit for the data ($\chi^2(1) = 0.000$, $\text{Prob} > \chi^2 = 1.000$).

Summary

In this chapter the researcher collected and analyzed historical data to answer each of the four research questions presented in this study. The researcher conducted a binary logistic regression analysis for each research question in order to identify the predictive power that the independent variables (instructor employment classification, student gender, student race, first-generation status) had on the dependent variable in this study (academic success in a student's first attempt in MTH 099). The first regression model found that there was statistical significance between Adjunct Instructors and a student

achieving academic success in the course when compared to Graduate Teaching Assistants, meaning a student is more likely to be successful in MTH 099 with Adjunct Instructors rather than Graduate Teaching Assistants. While the regression model showed a positive odds ratio for Lecturers compared to Graduate Teaching Assistants and a negative odds ratio for Lecturers compared to Adjunct Instructors, neither of these findings was statistically significant.

The results of the first regression models for the second research question found that a male student outcomes and an instructor's employment classification was not statistically significant in relation to a male student successfully completing MTH 099. The results of the regression model for female students showed statistical significance between female student outcomes and an instructor's employment classification. In the regression model for female students, the odds ratio of passing the course was positive for female students enrolled with an Adjunct Instructor, but was negative when comparing Lecturers to Adjunct Instructors. These findings suggest that female students would be more likely to succeed in MTH 099 when enrolled with an Adjunct Instructor instead of either a Graduate Teaching Assistant or Lecturer. Overall, gender was still found to be statistically significant with females having higher predicted odds of passing the course than male students.

The third regression model found that a student's race and instructor employment classification to be statistically significant in a student's odds of successfully completing MTH 099 with students who identified as having two or more races having the lowest odds of passing the course. The general regression model for this research question

comparing students racially and using White students as the comparison showed lower predicted success for Hispanic and multiracial students, but no statistical significance was found for Black students. Furthermore, there was no observable within-group difference among racial groups based on instructor classification.

Finally, the fourth regression model explored the predictive power of a student's first-generation status and an instructor's employment classification on a student's ability to achieve success in MTH 099, with Adjunct Instructors and first-generation status showing statistical significance when compared to Graduate Teaching Assistants. When Lecturers were compared against Adjunct Instructors in the regression model, students had a negative odds ratio for successful completion, yet this was not found to be statistically significant.

CHAPTER V

Conclusions, Discussions, Implications, and Recommendations

Introduction

This chapter presents a summary review of the previous four chapters and discusses the findings from Chapter IV in relationship to the context of the study and the existing literature in the field. The findings from Chapter IV will be examined and the implications from the findings will be discussed. Next, the limitations of the study will be outlined and recommendations for future research will be presented. Finally, conclusions will be presented in summarizing the research study.

Summary of the Study

The purpose of this study was to explore the predictive power between an instructor's employment classification and a student's gender, race, and first-generation status, as measured by final semester grades in developmental math. Specifically, the research examined whether an instructor's employment classification had an impact on a student's ability to reach academic success in their first attempt in MTH 099 during the period between 2013 and 2017. Four research questions guided this study:

1. Does an instructor's employment classification predict a student's academic success (receive a grade of C or better) in developmental mathematics?

2. Does an instructor's employment classification and a student's gender predict a student's academic success (receive a grade of C or better) in developmental mathematics?
3. Does an instructor's employment classification and a student's race predict a student's academic success (receive a grade of C or better) in developmental mathematics?
4. Does an instructor's employment classification and a student's first-generation status predict a student's academic success (receive a grade of C or better) in developmental mathematics?

The results of the statistical tests of the four research questions demonstrated that there is a correlation between an instructor's employment classification and a student's gender, first-generation status, and race in predicting academic success in developmental math, as measured by final grades. Overall, there was a statistical significance of student success for students enrolled in MTH 099 with Adjunct Instructors instead of Graduate Teaching Assistants. A student's gender, race, and first-generation status were all found to be statistically significant in predicting a student's success in MTH 099 based on instructor employment classification. As college readiness standards increase in the future, it is important that institutions develop an understanding of how students fare in developmental coursework and how instructor qualities play a role in a student's success in developmental courses in order to provide equitable opportunity for degree attainment.

While the existing research provided conflicting studies on the effectiveness of developmental mathematics, the role of the faculty within the classroom, and how student

characteristics affect a student's ability to be successful within a developmental math course, this research suggests that a student's race, gender, first-generation status and the instructor's employment classification all affect a student's ability to be successful in developmental mathematics. A deeper examination of the results of Chapter IV will be explored in the next section of this chapter.

Discussion of the Study

The descriptive data of this research shows a disproportionately high use of part-time faculty, as 81% of the students enrolled in MTH 099 were taught by a Graduate Teaching Assistant (70.8%) or an Adjunct Instructor (10.2%). This data aligns with Bettinger et al. (2013) in that most institutions employ a higher rate of part-time instructors for developmental courses. In looking at the descriptive data of grade breakdown by instructor level, only 31.73% of the students enrolled in MTH 099 with a Graduate Teaching Assistant successfully passed the course in their first attempt, 33.79% of students passed the course with a Lecturer, and the highest pass rate of 40.10% of students was with an Adjunct Instructor. Burgess & Samuels (1999) found that students who had a part-time instructor for developmental courses fared better than those who a full-time instructor. This descriptive data regarding Adjunct Instructors would tend to align with that research as they had a higher pass rate than the full-time employment of the Lecturers.

A contrasting difference in this data is found in how many students earned a grade of RQF (remedial quit failing) among the three instructor employment classifications. 91 students earned an RQF with a Lecturer, 31 earned an RQF with an Adjunct Instructor,

and 302 students earned an RQF with a Graduate Teaching Assistant. These numbers suggest that more students quit attending the developmental course when they are assigned a Graduate Teaching Assistant than those who are assigned any other instructor level.

Several research studies have identified that the students who are most likely to enroll in developmental math courses are first-generation, low-income and minority students (Bailey et al., 2005; Bettinger et al., 2013; Epper & Baker, 2009; Polk-Conley & Squires, 2012). In considering student characteristics related to this research data, the majority of students enrolled in MTH 099 identified their race as Two or More (30.48%) with White students being the second largest population (27.79%). Black or African American students comprised 20.91% of the population and only 18.94% of the students in MTH 099 were Hispanic. In looking at the descriptive data for how races fared in MTH 099 among instructor levels, all races had higher pass rates with Adjunct Instructors as opposed to Graduate Teaching Assistants or Lecturers.

The descriptive data for gender showed an overrepresentation of female students in MTH 099 who had higher pass rates with Adjunct Instructors, while male students had higher pass rates with Lecturers. Finally, descriptive data for first-generation students enrolled in developmental math aligned with literature in showcasing an overrepresentation of first-generation students in MTH 099 (60.45%). Both first generation and non-first generation students had higher pass rates in MTH 099 with Adjunct Instructors as opposed to the other instructor levels. Overall, the descriptive data for this research aligned with previously related research in showing a heavy reliance on

part-time faculty, high enrollment of minority students and an overrepresentation of first-generation students in developmental courses.

The findings of the logistic regression for the first research question shows that there is a relationship between an instructor's employment classification and a student's success in MTH 099. For students enrolled in MTH 099 with Adjunct Instructors instead of Graduate Teaching Assistants, the odds ratio increased by a factor of 1.44 and was statistically significant. Additionally, the odds ratio increased as well if a student were enrolled in the course with a Lecturer as opposed to a Graduate Teaching Assistant, but the finding was not statistically significant. Finally, the odds ratio decreased by a factor of .7622 for students enrolled in the course with a Lecturer instead of an Adjunct.

However, this finding was not statistically significant.

When the regression compared Lecturers to Adjunct Instructors, a negative odds ratio was present but the finding was not statistically significant. Overall, the regression model for these variables was not statistically significant ($\text{Prob} > \chi^2 = 0.0650$) yet in previous research it has been found that there are negative effects on retention of developmental students who were enrolled with part-time faculty (Jacoby, 2006). Additionally, in a regression analysis conducted by Penny and White (1998), students who were enrolled in developmental math with a full-time instructor fared better in their college level math course than those students who were enrolled in developmental math with a part-time instructor. Considering that this research question provides grounding for evaluating the use of part-time instructors versus full-time instructors, the literature review discusses instructor training concerns that could positively enhance student

outcomes in the course (Ashby et al., 2011; Bonham & Boylan, 2011; Sierpiska et al., 2008; Zavarella & Ignash, 2009). Overall, as student success increases when the instructor employment classification increases from a Graduate Teaching Assistant to an Adjunct Instructor or Lecturer within the first model, which raises a new question related to the professional development for the remedial mathematics instructors in identifying any differentiated approaches based on instructor employment classification.

The findings of the logistic regression for the second research question shows that there is a relationship between an instructor's employment classification and a student's gender and academic success in MTH 099. Gender has been found in research as a related variable to a student's progression in developmental education (Bailey et al., 2010). The data for this research predicts that male students are less likely to pass MTH 099 than female students, as the odds ratio is .50 and is statistically significant. Early research related to gender and academic success in developmental mathematics found no statistical significance between the two variables (Bean & Metzner, 1987; Penny & White, 1998; Umoh et al., 1994). However, in this research it was found that female students had a more positive affect than men from developmental mathematics, which aligns with similar studies (Bettinger et al., 2013; Long & Calcagno, 2011).

In earlier research it was found that the racial enrollment of developmental education programs is proportionately high for minority students (Attewell et al., 2006). In considering the findings of the logistic regression for the third research question, unlike previous research regarding African-American students enrolled in developmental math compared to White students, this research model does not predict any statistically

significant relationship between academic outcomes when compared to the measurement group of White students (Attewell et al., 2006; Bettinger et al., 2013; Penny & White, 1998). However, when reviewing the outcomes for Hispanic students, this model shows that they are .467 times less likely (or roughly 47% as likely) than White students to pass MTH 099. As Hispanic students have been found to be overrepresented in developmental courses, studies also show that less than ten percent of Hispanic students complete a post-secondary degree (Brickman et al., 2013; Chen & Carroll, 2005; Pike & Kuh, 2005; Solorzano & Ornelas, 2005; Villalpando, 2010). This research data adds to the compounding difficulties of this student population in identifying potential reasons why Hispanic graduation rates are low.

An interesting finding of this study within the third logistic regression was related to the student population that identified as two or more races. This student population was found to have an odds ratio showing that they are .0367 times as likely as White students to successfully complete the remedial math course. When reviewing the descriptive data for this research, it was found that students with two or more races were the majority race represented in this study, yet the least likely to pass the course with a pass rate of 3.74%. Furthermore, there was no observable within-group difference among racial groups based on instructor classification. Overall, the regression model in determining the odds of student success as it relates to the instructor's employment classification and the student's race was found to be statistically significant in predicting student outcomes (Prob > chi2 = 0.000).

The findings from the final research question indicated that there is a relationship between an instructor's employment classification and student's first-generation status in predicting a student's academic success in MTH 099. Research has found that the majority of students who are enrolled in developmental math tend to be first-generation students (Bailey et al., 2005; Epper & Baker, 2009; Chen, 2005). Additionally, first-generation students have been found to be more likely than non-first generation students to enroll in the course multiple times due to not meeting passing requirements (Choy et al., 2000; Ishitani, 2006; McCarron & Inkelas, 2006). However, the results from this data show that overall first-generation students are more likely to pass MTH 099 on their first attempt (34.85%) than non-first generation students (30.10%). Furthermore, the complete logistic regression model predicted that first-generation students are 1.08 times more likely to be successful in MTH 099 than non-first generation students. Overall, this regression model with the first-generation status and instructor employment classification variables in predicting academic success in MTH 099 was found to not be statistically significant ($\text{Prob} > \text{chi}^2 = 0.0531$).

In combining all variables into one logistic regression model to search for additional findings, the data output remained the same in validating the previous logistic regression models. White students when compared to all other races had statistically significant higher odds ratio of passing MTH 099 by a factor of 3.0051. Gender outcomes for the holistic regression model were similar in outcomes in the previous logistic regression models. Males were found to be .501 times as likely than female students to pass MTH 099 which was found to be statistically significant ($\text{Prob} > \text{chi}^2 =$

0.000). Finally, first-generation outcomes in this model showed that these students were to be 1.0829 times more likely to be successful in MTH 099 than non-first generation students, but was not statistically significant.

Overall, the complete regression model indicated that there is a relationship between an instructor's employment classification and a student's race, gender, and first-generation status in predicting academic success in MTH 099. The marginal effects for the complete regression model predicted the odds of passing the course with an Adjunct Instructor instead of a Graduate Teaching Assistant increased 8.51% and was shown to be statistically significant at the 5% level ($P > |z| = .029$). Students who were enrolled with a Lecturer instead of a Graduate Teaching Assistant had a 1.41% higher chance of passing the course, and students who were enrolled with a Lecturer instead of an Adjunct Instructor had a 6.46% decreased chance of passing the course; neither of which these findings were shown to be statistically significant.

In examining the marginal effects further in the holistic regression model, White students were found to be 25.21% more likely to pass the course than all other races, which was shown to be statistically significant ($P > |z| = .000$). Male students were found to have a decreased 14.23% chance of passing the course when compared to female students, which was also shown to be statistically significant. Finally, first-generation students had a 1.72% chance of being more successful in MTH 099 when compared to non-first generation students, but the finding was not statistically significant.

In concluding the findings of the four research questions, the data adds to the current body of literature in highlighting that student success in developmental math can

be attributed to the instructor's employment classification, a student's gender, race, and first-generation status. Additionally, these findings indicate that quantitative outcomes based on the variables in this research can guide institutions in supporting additional research related to their developmental educations in rectifying achievement gaps.

Implications

The finding that instructor employment classification, student race, gender, and first-generation status all predict a student's success in developmental mathematics should challenge post-secondary math educators and higher education administrators to consider how to foster optimal learning environments with these variables in mind. As mentioned by Pruett and Absher (2015), developmental students have higher attrition rates than non-developmental students and in order to address such rates, university personnel should evaluate academic advising, tutoring, and classroom engagement efforts to assist students in connecting with course material and addressing needs (Bettinger et al., 2013). By rejecting the idea that underprepared students should not be enrolled in higher education, university leaders can begin to question current practices related to development math programs and how to create an inclusive and optimal environment for student success.

These findings begin to open the door for post-secondary math educators and university administrators to explore how current developmental programs are coordinated in identifying areas for improvement, as related to employment practices, training practices, and classroom engagement; all of which support the same ideas presented by Bettinger et al. (2013) and Bonham & Boylan (2011). Specifically related to math, the

standard of professionalism suggested by The American Math Association for Two Year Colleges (2006) suggests that developmental math instructors should have specialized training and teaching preparation. Considering the pass rates of developmental math students, this standard should be prevalent for all institutions of higher education to ensure that instructors are receiving the necessary professional development to assist students in content mastery.

The institution under study solely relied on placement exam scores to determine a student's beginning level of developmental math. Yet, research has suggested that colleges are too quick to enroll students into developmental courses without considering additional variables (Bettinger et al., 2013). Therefore, institutions such as the one under student should begin to explore various means for holistically placing a student in a developmental education program. One placement model that should be considered by university administrators is the T.I.D.E.S approach (targeted intervention for developmental education students) as posed by Boylan (2009). As related to employment practices, research has suggested that the most successful developmental education programs employ a higher percentage of full-time instructors, yet this data set suggests that Adjunct Instructors have a higher success rate than Lecturers (Boylan 2002; Boylan & Saxon, 1998). As this finding adds to the current variance in other findings, institutions should focus on how they equip developmental educators, whether part-time or full-time, with research-based practices and new approaches in providing an optimal opportunity for success and understanding for the students (Boylan, 2002; Epper & Baker, 2009; Bonham & Boylan, 2011).

Additionally, this research found that 71.22% of the students chose to quit attending a course taught by a Graduate Teaching Assistant, as opposed to any other employment classification. Overall, 70.8% of the students enrolled in developmental math were assigned to Graduate Teaching Assistants. While this is not a significant difference, these findings should guide university leaders towards the enhancement of training procedures if Graduate Teaching Assistants will be utilized as instructors of developmental education, as indicated in previous research (Kinney, 2001; Schnee, 2014). Doing so can enhance the classroom environment by equipping developmental educators with the necessary pedagogical skills to assist students towards content mastery (Bonham & Boylan, 2011).

As this research connects to the findings of Jacobs (2012), who argued that funding should be emphasized for students to attend community colleges to be remediated as those institutions were viewed to be more equipped in serving underprepared populations, four year institutions should see opportunities to partner with two-year colleges to better serve their student needs. While remedial education is a potential revenue source for four-year institutions, the research and the findings of this study show that students are being poorly served by Graduate Teaching Assistants or other instructors who are not properly trained pedagogically to serve underprepared students in the ways that two-year colleges are. The implication of this finding should encourage four year schools to move away from remediation entirely and instead partner with institutions that can better serve populations most at risk to need additional help with mathematics.

Finally, the findings of this data related to racial implications of academic success in developmental mathematics should guide university administrators towards exploring ways to address not only the overrepresentation of minority students in developmental programs, but appropriate means to assist the students in being successful in the course. Literature related to minority students' success in developmental education is stemmed around fostering student learning and engagement with mathematical concepts through writing assignments, specifically related to English Language Learners (Loud, 1999; Meier & Rishel, 1998; Pugalee, 1997). While literature has found that the Hispanic population has been found to be highly overrepresented in developmental courses (Brickman et al., 2013; Chen & Carroll, 2005; Pike & Kuh, 2005; Solorzano & Ornelas, 2004). However, in this research the Hispanic population was the least represented race but had the second to lowest pass rate overall and was found to have a 12.46% lower chance than White students for passing the course. By understanding an institution's demographic of developmental mathematics students, university administrators can provide appropriate pedagogical tools to instructors to use in a tailored fashion for student types in order to propagate success.

Recommendations for future research

The purpose of this binary logistic regression study was to explore the predictive power between an instructor's employment classification and a student's gender, race, and first-generation status, as measured by final semester grades in developmental math at regionally accredited state institution of higher education in Texas. The results of this research should provide insight for researchers interested in studying how an instructor's

employment classification influences a student's success in developmental mathematics in focusing on closing educational gaps and promoting academic success. Future researchers could apply this statistical model to other institutions who have developmental math programs, perhaps at the community college, junior college, and private school levels. The more data collected on instructor employment classification, student race, gender, and first-generation status as it predicts success in developmental math courses, the more findings will accurately reflect trends in how students fair in developmental math.

Future research on success rates in developmental math programs should also take advantage of collecting additional demographic variables related to the instructor. Researchers should consider how the instructor's gender and race might influence a student's ability to success in developmental math, rather than solely focusing on student demographics. Additionally, an instructor's employment classification does not necessarily depict an instructor's experience level. Therefore, researchers should consider collecting data over instructor educational level, years of instructional experience at the higher education level and the secondary education level, and if the instructor has completed any pedagogy trainings related to developmental education from professional development math organizations and associations. Even data related to student attendance and how it relates to an instructor's employment classification could provide context to a student's success in developmental mathematics, as well. One of the challenges for future researchers is to avoid looking at short term effects of instructor variables on student success in developmental mathematics as to avoid making

generalizations, rather focusing on long term data from a variety of institutions to portray any present trends related to student outcomes.

In this research, the overrepresentation of students who identified as two or more race and failed developmental mathematics in comparison to other student populations implies a need for additional research to this population. Previous research studies related to a student's race and success in developmental education have identified African-American and Hispanic students as students who perform at lower rates than the White student populations (Attewell et al., 2006; Bettinger et al., 2013; Villalpando, 2010). Additional research in the relation of student race to academic success in developmental education would allow for a better understanding as to if the finding of high failure rates of students who identify as two or more race is unique to the institution and region under study, or if there is an apparent pattern at other Texas state institutions.

Finally, this research focused solely on quantitative implications through a binary logistic regression analysis. In order to provide additional context to determining the best factors in predicting a student's success in developmental mathematics, future research should consider a mixed-methods approach in conducting student and instructor interviews to identify any themes present. Previous research has found that the learning environment created by the instructor of the course affects student completion rates in developmental mathematics (Ashby et al., 2011; Zavarella & Ignash, 2009). Expounding on this research in comparison to instructor and student perceptions of the learning environment can add to the quantitative outcomes in addressing needs.

Concluding Remarks

This research study attempted to explore the relationship between an instructor's employment classification and student success in developmental mathematics in order to fill a gap in previous literature related to student outcomes in developmental courses. Using the appropriate statistical model and research design based on what earlier researchers have employed, this study focused on a certain set of quantifiable instructor and student variables to highlight unique issues related to developmental education at the higher education level, specifically in mathematics. In doing so, this study attempted to provide a predictive model for determining student success in developmental math courses while using the variables under study to be utilized for application with other institutions of higher education.

This study provided a unique focus on a Division 1, regionally accredited state institution of higher education in Texas. This perspective can be examined from similarly sized institutions who reside in similar geographic locations. While this is a narrow focus, the results of this study does reveal patterns within the developmental math program at the institution under study for university leaders to evaluate and assess in enhancing developmental efforts. Therefore, these results could also inform institutional leaders at similarly sized and regionally located universities in relation to their developmental programs. Overall, state institutions within Texas can all garner useful information from this study about the role that an instructor's employment classification, student gender, student race, and first-generation status play in a student's success in developmental mathematics.

As developmental education continues to act as a gate keeper to higher education, the attrition rates of students enrolled in developmental courses will continue to be a topic of discussion. As Pruett and Absher (2015) found that students enrolled in developmental education have the highest attrition rates compared to other student populations, university and educational leaders will need to critically evaluate the cause of such attrition rates and the impact that is being made on additional rates, such as retention and graduation rates. The outcomes of this research continues to highlight the concern regarding pass rates of developmental math students, similar to Boatman and Long (2010) as they specifically found that this student population had lower college completion rates. As the research of Boatman and Long (2010) was discovered eight years ago, this research still shows that pass rates are a continued issue with these students and should be a concern to higher education administrators and practitioners in calling into question why this might be.

Considering the current research in the field of developmental education and the various conclusions researchers have come to in regards to student success in developmental courses, it should come as no surprise that state and institutional leaders will continually be forced to evaluate current policies, practices, and procedures to enhance developmental outcomes. Empirical research related to student outcomes in developmental courses will serve as a driving factor in identifying educational gaps across student populations. In utilizing such research, realistic changes in how developmental programs are coordinated will be a frequent topic of discussion and research in identifying the best practices for university administrators and instructors.

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APPENDIX A

From: Brittany Fish
Sent: Monday, June 12, 2017 6:04 PM
To: Lynda S. Langham
Subject: Dissertation Data Request

Good evening Lynda,

First, let me thank you for meeting with me nearly two weeks ago to discuss the research I am conducting for my dissertation and guiding me in the appropriate direction in obtaining my data. I apologize for the delay of this e-mail requesting approval for the data, as summer time tends to be our busiest time.

My dissertation research considers the influence that an instructor's employment classification status has on a student's academic success in Math 099, as determined by final semester grades. The data requested for this research aligns with the current WebFocus report sad433_tsi_developmental_grades (sheet 2 of the report) developmental is spelled incorrectly in the report).

In order to ensure anonymity and confidentiality of students and instructors, I would like to request that Tristan modify the report to delete student ID numbers and student email addresses, and replace the student names with a number value (1 through X amount).

Additionally, I would like to request that a new column is to be created next to the CRN column with the identifying instructor's employment classification for that term, as some instructors may have received promotions etc. As the researcher, I will code the grades and instructor employment classifications numerically in order to run a binary logistic regression utilizing SPSS to determine if an influence exists.

The university will not be named within the study, as I will use a pseudonym. Please let me know if I need to provide anymore clarifying information.

I appreciate all of your help!
Brittany Fish

APPENDIX B

Informed Consent Form

“Developmental mathematics: A quantitative investigation of instructor classification as related to student success.”

Dear participant,

My name is Brittany Fish and I am a doctoral student at Stephen F. Austin State University in Nacogdoches, Texas. I am currently working on a study titled, “Developmental mathematics: An epidemic or systemic oppression? A quantitative investigation of instructor classification as related to student success” and need your help in collecting information for my research. Participation in this study is strictly voluntary and you have the right not to participate. The purpose of this research project is to identify why type of influence exists between an instructor’s employment classification and a student’s gender, race, and first-generation status, as measured by final semester grades in developmental math.

In order to obtain information for this research, archival data will be collected from the university’s Office of Institutional Report. Data collected will be aggregated and analyzed through the SPSS system. If you choose, the institution may have access to the data collected and the analytical reports created. Data are to be collected and analyzed before the end of December 2017.

Confidentiality will be maintained at all times. The institution’s name, personal information, and place of residency will not be disclosed at any point. The institution’s name will not be associated with any part of this study, as pseudonyms will be used if the institution needs to be addressed. In addition to this, all data collected during this process will be kept in locked cabinet within my home and will be destroyed six months after the completion of my research.

Additionally, you may decide to discontinue your participation in this research project any point during the completion of the study. I will be happy to share the findings of the research after the study has been conducted. I sincerely appreciate your help in completing this study and thank you for your participation and time.

By signing my name, I am stating that I agree to participate in this research study.

Participant’s name

Brittany Fish

Doctoral Candidate

Department of Secondary Education & Educational Leadership

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Participant’s signature

Date

VITA

Brittany A. Fish has worked in higher education for over five years as an admission counselor and academic administrator. She attended Stephen F. Austin State University where she received a Bachelor of Science in Hospitality Administration in 2012. She immediately began working in the admissions field of higher education while she pursued a Master of Science in Human Sciences at Stephen F. Austin State University, which was conferred in 2015. In 2014, she transitioned to academic advising and began working with high needs students, such as undeclared and developmentally liable students. In 2015, Brittany was accepted into the Doctorate of Educational Leadership program at Stephen F. Austin State University, where she earned her Doctorate in 2018. Currently, she serves as an Academic Advisor, Instructor of Human Sciences, and Instructor of SFA 101 and SFA 110 at Stephen F. Austin State University.

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Style manual designations	<i>Publication Manual of the American Psychological Association, Sixth Edition</i>
Typist:	Brittany A. Fish