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Examination of Student, Instructor, and Classroom Characteristics to Predict Success in Elementary Algebra at Shawnee State University

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SHAWNEE STATE UNIVERSITY

Examination of Student, Instructor, and Classroom Characteristics to Predict Success in Elementary Algebra at Shawnee State University

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The thesis entitled '**Examination of Student, Instructor, and Classroom Characteristics to Predict Success in Elementary Algebra at Shawnee State University**' presented by **Chelsey A. Thompson,** a candidate for the degree of **Master of Science in Mathematics,** has been approved and is worthy of acceptance.

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ABSTRACT

There is a high emphasis on gaining a college education in order to prosper and be successful in life. Student success is a high priority to all institutions, but many students enroll into college lacking the basic skills required for college level courses. This is especially true for mathematics. Developmental education started off as tutoring, however, it grew into something more than tutoring alone. Developmental courses were created to help students gain those basic skills so that they can take college level courses and hopefully obtain a college degree. There are concerns with students dropping out without a degree due to the financial burden and frustration related to taking developmental courses. This study seeks to see if there are any areas of improvement that should be made to developmental mathematics courses by examining a group of predictors. A group of predictors consisting of student characteristics, instructor characteristics, and classroom characteristics were selected to analyze. Student characteristics include gender, age, race, ACT Math score, ACT Reading score, math pretest score, 1st generation status, SES, and high school GPA. Instructor characteristics include gender, degree, and employment status. Classroom characteristics include class size, number of times a class meets per week, and time of day the class meets. The dependent variables in this study will be final exam score and overall grade in the developmental mathematics course. The theoretical framework of this study is Tinto's Theory of Retention which seeks to find out why students drop out of college. In Tinto's theory, students enter college with a background that could affect the way they integrate into college ultimately leading to the decision to stay in college or drop out. Meaning that if a student doesn't integrate into college, then that could lead to a decision to leave college. Knowing what the predictors of success are for developmental mathematics is beneficial so that any improvements can be made to the course to help students be more successful and thus help students complete college. The sample consists of students who were previously enrolled in a developmental mathematics class at Shawnee State University, Math 0101: Basic Algebra with Geometry Application. The research design of this study is ex-post facto which means that the data already existed, but needed to be collected according to the needs of the study. Data came from student records, department records, class schedules, and from the Director of Developmental Mathematics at Shawnee State University. Regression and ANOVA techniques were implemented to examine the predictors. Standard logistics regression followed up by forward selection logistic regression was used to see any predictors were significant in predicting success in the course. The forward selection logistic regression model was a better fit model compared to the standard logistic regression based off the Akaike information criterion (AIC) and chi-square model comparison. ACT math score, pretest score, high school GPA, class size, and SES (determined by Pell-Grant status) were the predictors that remained in the reduced model. However, Pell-Grant status was not significant even though it remained in the model. There were no significant predictors in the multiple regression models in predicting for the final exam score. Relating back to the theoretical framework of this study, the predictors that were significant in predicting success in the course were all in the pre-college schooling background category. Institutions and the instructors of the developmental mathematics course can keep this in mind when making decisions about the course and help students to be successful in the developmental mathematics course, thus helping them succeed in their college career.

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CHAPTER I: Introduction

Chapter 1 will include an introduction to predicting success in developmental mathematics courses and the importance of developmental mathematics. Chapter 1 will also include background on the topic, research questions being investigated, research hypotheses, and the significance and purpose of the study. The chapter will end with an overview of the research design and overall organization of the thesis.

Introduction

There is a high emphasis on obtaining a college education in order to be able to not only make a living, but to prosper and to be successful in life. Many students enter into college not ready for college level courses and need additional instruction to reach that level. This is especially true for mathematics. Developmental courses were created to aid students so that they can take college level courses and reach the goal of completing college and obtaining a career where they will thrive. ACT reported that only 26% of high school graduates who took the ACT were ready for college level courses in all four areas which are English, reading, math, and science. Additionally, only 39% of high school graduates who took the ACT met the mathematics College Readiness Benchmark in 2019 (2019).

Institutions want students to be successful and to graduate with a degree. While developmental mathematics courses were created to help students, many students still don't complete the course. Martinez reported in his study that between 2008 and 2013 that a little over half of the students enrolled in a developmental mathematics course voluntarily dropped or didn't persist through the course (2017). How can institutions help students to be successful in their developmental mathematics courses and increase their chances of obtaining a degree? This study hopes to find useful information about potential predictors of success in developmental mathematics which could provide a clue on how to help students succeed.

Background

Student success is a high priority to all colleges and universities. Many students are underprepared for college level mathematics course and so developmental mathematics courses were created as an intervention to improve students' mathematics skills. Brasiel found that supporters of developmental mathematics say that students can benefit from taking a developmental mathematics course, especially those "marginalized populations" (2017). However, there are people who do not support developmental mathematics courses. Critics of developmental mathematics say that it can hinder student success for reasons including it taking more time and money for the students who had to take additional coursework that didn't contribute to their degree thus potentially resulting in students not completing their degree (Brasiel, 2017).

In order to improve the developmental mathematics course, it is important to identify what factors contribute to developmental student success (Martinez, 2017). Knowing what these predictors are could save universities time and money (Hunt, 2011). Potential predictors of success, which are characteristics of students, instructors, and classrooms, were selected to be examined in this study. There has been evidence found that some of these predictors can predict success in developmental mathematics, but there are conflicting views as well.

Student characteristics include gender, age, race, ACT Math score, ACT Reading score, math pretest score, 1st generation status, Socioeconomic Status (SES), and high school GPA. Gender was to be significant or non-significant relating to predicting success. Those studies that found gender to be significant either found males to be more successful than females or found females to be more successful than males. For example, Hunt for gender to be a good predictor of success in developmental mathematics courses while Martinez found that gender was not a good predictor of success in developmental mathematics (2011; 2017). There are also conflicting findings relating to ACT math score. ACT Math covers pre-algebra, elementary algebra, intermediate algebra, coordinate geometry, plane geometry, and trigonometry. Stephens found ACT mathematics score to be non-significant while Hunt found ACT mathematics score to be a significant predictor (2005; 2011). Pretests are in-house created tests that are given to students so that their knowledge gained in the course can be measured or analyzed. Many studies include this variable in their research and have found them to be significant including Hunt (2011). Age is categorized into two groups: traditional college age and non-traditional college age. Research has found age to be significant in predicting success including Wolfe (2012). 1st generation college students face challenges including poor preparation academically and inadequate funds due to lack of support (Engle, 2007). Engle also argues that when transitioning into college that 1st generation students are at most risk (2007). Examining 1st generation status as a predictor of success in a developmental math course will help fill the gap of knowledge on this topic and help all students to succeed in college. Examining ACT reading score will also help fill that gap which Hunt recommended to examine that variable in her study (2011). Socioeconomic status, determined by Pell Grant eligibility in this study, was found to influence student achievement (Aydin, 2017). Students with low socioeconomic backgrounds are less prepared entering into college and more likely to take developmental mathematics (Atuahene, 2016).

Instructor characteristics include gender, degree, and employment status. Part-time faculty typically has less institutional knowledge compared to full-time faculty. However, Ran found in a survey that this difference between part-time and full-time faculty didn't directly affect students' academic achievement (2019). Contradicting that finding, employment status was found to be significant predictors of success in developmental math (Hunt, 2011). Instructor gender was also found to be significant in Hunt's study (2011).

Classroom characteristics include class size, number of times a class meets per week, and time of day the class meets. Time of day is categorized into two groups, morning (A.M.) and evening (P.M.). All three of these variables were found to be influential on student achievement. Fong found that smaller class sizes were associated with greater chance of academic success (2015). Hunt found time of day and class size was found to be significant predictors of success in a developmental math course.

Statement of the Problem

A college education is very important and is the key to success in many cases (Hout, 2012). Since college education is so important, there is a great deal of focus on preparing students for college level education. There is concern with the college readiness of students, particularly in mathematics. This study selected a group of variables to be analyzed that could be potential predictors of success in developmental mathematics. Knowing what these predictors are could lead to better institutional decisions regarding developmental mathematics and thus help students succeed in their college career. Based on the examined predictors, are there areas of improvement to the developmental math course that need to be made so that student success and student retention increases?

Purpose of Study

The purpose of this study is to reveal areas of possible improvement to developmental mathematics courses by examining potential predictors of success. Universities want their students to succeed and for student retention rates to increase. Information found in this study can lead to decisions by administrators to improve developmental mathematics courses. This study will examine characteristics of students, instructors, and classrooms to see if any are good predictors of success in developmental mathematics. The dependent variables are final exam score and overall grade in the developmental mathematics course.

This study is based on a previous study conducted by Linda Hunt in 2011 at Marshall University Community and Technical College. She recommended analyzing age, high school GPA, financial need, and reading ability measured by ACT or SAT as potential predictors of success in developmental mathematics. Those variables will be analyzed in this study. Additional variables that weren't tested in her study include 1st generation status, graduate student level in the employment status, instructor degrees, and student race.

This study is quantitative and any categorical variable will be recoded accordingly in analysis. How the variables are recoded will be explained thoroughly in Methodology. Overall grade in the course will be categorized by passing (C or higher) and failing (below C). The research design is an ex-post facto design where the events had already occurred and were recorded to where the data can be analyzed in the future. Population under study are college students who were enrolled in a developmental mathematics course (Math 0101: Basic Algebra with Geometry Application) at Shawnee State University.

Significance of Study

The significance of examining potential predictors of success in developmental mathematics is very important considering many students enter college lacking the basic skills in mathematics that is needed for college level mathematics. Hunt and Martinez acknowledged in their studies that it is important to know what the predictors of success are in developmental mathematics since there are many students who need remediation in mathematics (2011; 2017). Achieve reported that about 40% of graduates lacked skills that affected their performance in college and in the workplace and also had gaps in their mathematical knowledge (2014). Since institutions want students to succeed and for retention rates to improve, developmental mathematics was created to fill the gap of knowledge many students lack. Any information gained about predictors of success in remedial mathematics can help administrators strategize on how to improve remedial interventions and thus improve student retention rates and college success (Martinez, 2017).

Research Questions and Hypotheses

1. Are student, instructor, and/or classroom characteristics predictive of success in developmental math courses?

Hypothesis: ACT Math score, math pretest score, ACT Reading scores, and HSGPA will be significant student predictors. Employment status will be a significant instructor predictor. Number of class meetings in a week will be a significant classroom predictor.

2. Are student, instructor, and/or classroom characteristics predictive of success on the final exam?

Hypothesis: ACT Math score, math pretest score, ACT Reading scores, and HSGPA will be significant student predictors. Employment status will be a significant instructor predictor. Number of class meetings in a week and time of day will be significant classroom predictors.

3. Is the student predictor Race X SES a significant predictor of success in a developmental mathematics course when controlling for High School GPA?

Hypothesis: Race X SES will be statistically significant when controlling for high school GPA.

4. Is the student predictor Race X Gender a significant predictor of success in a developmental mathematics course when controlling for High School GPA?

Hypothesis: Race X Gender will be statistically significant when controlling for high school GPA.

5. Is the student predictor SES X First Generation Status a significant predictor of success in a developmental mathematics course when controlling for High School GPA?

Hypothesis: SES X First Generation Status will be statistically significant when controlling for high school GPA.

Research Design

The variables in this study are characteristics of the students, instructors and classrooms. Student characteristics include gender, age, race, ACT Math score, ACT Reading score, math pretest score, 1st generation status, SES, and high school GPA. Instructor characteristics include gender, degree, and employment status. Classroom characteristics include class size, number of times a class meets per week, and time of day the class meets. The dependent variables in this study will be final exam score and overall grade in the developmental mathematics course.

Students in this study were enrolled in a developmental mathematics course at Shawnee State University. For this study, the developmental mathematics course is Math 0101: Basic Algebra with Geometry Application. This course provides a foundation in basic mathematical skills for students who are weak in that area. Examining these predictors could shine light on the topic of student success in developmental mathematics which can help contribute to student success in their college careers and increase retention rates. Many students believe that their college education is the key to their career success and it is important to institutions that their students are successful.

Regression and ANOVA techniques will be implemented for analysis. Categorical variables, such as gender, will be recoded so that analysis can be run. Success in Overall Grade in the course will be recoded according to what is considered a success (C or higher is success/passing and below a C is failing). Logistic regression techniques will be implemented for the first research question due to the dependent variable being success in the course which is categorical. Multiple regression techniques will be used for research question 2 since there are multiple variables being considered in creating a model to predict final exam score. The last three research questions used similar techniques.

Theoretical Framework

The National High School Center at the American Institutes for Research reports that there exists a gap between students' expectations in attending college and their college readiness. Because of this, many students who attend a college do not graduate with a certificate or degree. It was estimated that 63% of high schools' graduating seniors were prepared for college level courses without the need for remediation and that 51% will graduate college. So, 37% of high schools' graduating seniors are not prepared for college level courses without remediation and 49% will not graduate college (2012).

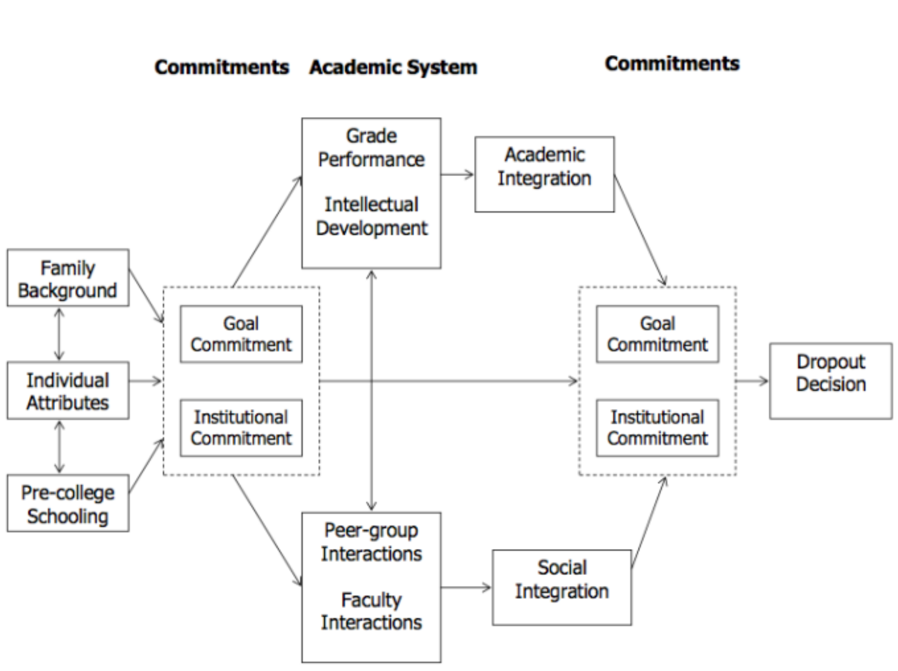
Since many students are underprepared in basic mathematics skills when entering college, developmental or remedial mathematics courses were created to help those students fill the gap so that they can be successful in college level courses. Over 40% of first year college students are enrolled in and complete at least one developmental mathematics course (Martinez, 2017). If students are more likely to be successful in their college level mathematics courses, then they are more likely to be successful in the rest of their college career. Colleges want students to be successful in their pursuit of a certificate or degree. It is considered a failure for a college if students leave without reaching their goal of a certificate or degree (Tinto, 2012). Students who are placed in developmental math courses can be considered to be at risk of failing and dropping out of college (Stephens, 2005). Boatman also states that developmental or remedial students are more likely to drop out of college before obtaining a degree (2018). Tinto argues that there are many reasons for students to leave a program or university. The reason that relates to this study most is students' inability to integrate academically into the college community during the first academic year (1988).

The theoretical framework for this study will be Tinto's Theory of Student Retention (1975). The Theory of Student Retention was developed with the goal of explaining why students dropout from colleges and universities. The theory's roots are in Durkheim's Theory of Suicide which claims that people are more likely to commit suicide if they are not integrated into society (Tinto, 1975). Tinto views college as a social system, which has its own values and social customs (1975). When viewing college as its own social system, dropping out of college can be viewed as a form of suicide when compared to an individual committing suicide in a larger community or society (Tinto, 1975).

Tinto names various characteristics that students come into college with including individual attributes (gender, race, ability), family background (social status, value climates), and precollege experiences (GPA, academic and social attainments) (1975). For this study, there are variables that are being analyzed that fit into those categories. Gender, race, age, and first generation status fit under individual attributes. High school GPA, ACT Math score, and ACT Reading score fit under precollege schooling. Socioeconomic status (SES) and first generation status fit under family background. Tinto suggests that these backgrounds and attributes affect how students preforms in college and impacts the development of educational expectations and commitments that they bring with them to college (1975). The expectations and commitments that students set for themselves and the college commitments are important factors in the student's experience in college. Goal commitment is referring to the determination a student has to complete college and obtain a degree. Tinto uses the example of someone who expects to obtain a doctoral degree will be more likely to persist to obtain a 4-year degree versus someone who would stop at the college level. Institutional commitment refers to the willingness to commit to a particular college a student is attending such as financial and time commitments (1975).

All students enter into college with some level of expectations and commitments (earning a degree, paying tuition, and etc). Students who have to take developmental courses enter into college with expectations and commitments as well. Developmental courses are non-credit courses, so they do not contribute to getting a degree. The fact that developmental students are willing to take a non-credit course adds another level to their commitment to obtaining a degree. The next part of Tinto's model is the integration academically OR socially into the college community. The integration academically or socially is crucial during the first academic year (1988). A limitation to this study is that not all students who take a developmental math course are first year students due to possible fear of mathematics or other reasons. Academic integration refers to grade performance and intellectual development. Social integration refers to interactions between the student and other people such as classmates and professors (1975). This study addresses the academic integration path of Tinto's model. A limitation to this study is that it does little to address the social integration. While the literature review will address aspects of the social integration, this study will not analyze those factors. Since students need to integrate academically or socially, then it is possible for students to only integrate in one of those ways and still succeed. This study will only address academic integration by the success in a developmental math course. Final Exam score and Overall Grade in the developmental mathematics course will be the measurement of academic integration. A limitation here in the study is that students most likely are in other courses and it doesn't acknowledge whether they succeed in those other courses or not. Regardless of that limitation, success in even just one course can increase the chances of success in students' college career. After integration into the college community, we are back to those goal and institutional commitments which leads to a decision to drop out or not. This study doesn't address whether a student decides to drop or not, but it does address factors that could lead to students making that decision. The more that is known about students' integration into the college community (academically or socially), the better decisions that can be made regarding the institutional decisions.

Figure 1: A Conceptual Schema for Dropout from College, (Tinto 1975)



<u>Assumptions, Limitations, and Scope</u>

It was assumed that all students had graduated from high school or obtained a GED. It is assumed that students' grades were an accurate illustration of their mathematical knowledge.

This study doesn't take into consideration the possibility that students in the developmental mathematics course are retaking the course due to not passing it the first time. There are a small number of instructors that teach developmental mathematics at Shawnee State University and so the characteristics of instructors of this study are limited to those instructors. Although it is assumed that the students' grades are representative to their mathematical knowledge, there is still the chance that a student's final grade may not appropriately represent their mathematical knowledge at the end of the course. Data from the year 2020 was not included in this study due to the effects of the global pandemic, Covid-19. However, the effects of Covid-19 on developmental mathematics and other courses could be a topic that is investigated in another study.

Generalizability to Shawnee State University might be problematic since demographics and academic attributes may not be representative of all developmental students. Note that the university this study was conducted at is located in the Appalachian region and so the students might be more representative to that population rather than urban areas. Shawnee State University is a public university in the state of Ohio. Careful consideration needs to take place when generalizing this study to private colleges and universities located in other states. Students in this study may not be representative of all developmental students in the state of Ohio. Shawnee State University is a smaller university with an undergraduate enrollment total of approximately 3,600, so take this into consideration when generalizing to larger universities with larger undergraduate enrollment. Plus, larger universities most likely have more instructors teaching developmental mathematics compared to Shawnee State University.

Definition of Terms

- Developmental Mathematics: For this study, the developmental mathematics course is Math 0101 (Basic Algebra with Geometry Application). Shawnee State University Course Catalog describes this developmental mathematics course as providing good background in arithmetic for students with little to no background in algebra and geometry. Math 0101 also is not included in the list of courses that count toward a degree (2020). Typically, developmental mathematics credit hours do not count toward degrees requirements or graduation and includes arithmetic, elementary algebra, intermediate algebra, and geometry (Hunt, 2011). Literature also uses remedial mathematics to describe this type of course (Wolfe, 2012).
- Success: Success is considered to be passing the Final Exam in the developmental mathematics course or passing the developmental math course. Success in the course was defined by obtaining a C or higher while failing the course was defined by obtaining a grade lower than a C (Stephens, 2005; Wolfe, 2012).

Summary

Many students are not prepared for college level mathematics when enrolling into college. The goal of developmental mathematics is to strengthen students' mathematical knowledge and background so that they will be able to take college level mathematics for the degree they are pursuing. Exploring predictors of success can enlighten institutions on how to help students succeed in their developmental mathematics course and thus helping them succeed in their college career. Tinto's retention theory is the theoretical framework of this study which will examine student integration academically through the form of a developmental mathematics course. Student integration academically and/or socially can determine if a student drops from college. This study will primarily focus on academic integration, but will address social integration in the literature review. While there are limitations to this study, this study will still expand on the knowledge of student integration academically and student success in college.

CHAPTER II: Background and Literature Review

Universities are committed to course success and maintaining high graduation rates. Many students enter college lacking the mathematical skills to take college level mathematics courses and so developmental mathematics was created. The history of developmental education will be reviewed in order to build a foundation of knowledge relating to developmental mathematics and where it began. Literature relating to the importance of developmental mathematics will also be reviewed since many students take these courses. There are areas of concern relating to low rates of success for students placed in at least one developmental course leading to students spending more time and money and taking out student loans and not being able to make loan payments. Literature relating to these risks and the high costs will be covered in this chapter. Tinto's Retention Theory argues that students have to adjust not only academically, but also socially in order to integrate into college life and be less likely to drop from college (1975). The social integration aspect of Tinto's Retention Theory will be reviewed in this chapter since this study does not directly analyze social integration from the theory. This study focuses more on the academic integration part of Tinto's Retention Theory. It is important to be aware of existing literature and studies focused on the predictors of this study so that a foundation of knowledge is built about these predictors. Once all of this information is reviewed, then there will be an overall review of where developmental mathematics came from and why developmental students take developmental courses and how these developmental courses can affect students and what can potentially affect these students' college success.

History of Developmental Mathematics

Developmental education began as early as the 20th century. Six phases of learning assistance history was established by Arendale and are as follows: Phase 1: 1600s to 1820s, Phase 2: 1830s to 1860s, Phase 3: 1870s to mid-1940s, Phase 4: mid-1940s to 1970s, Phase 5: early 1970s to mid-1990s, and Phase 6: mid-1990s to the present (2010). No remedial or developmental courses were offered to students in phase 1, but tutoring was available. When Harvard College opened in 1636, there was a need for remediation because all instruction was in Latin and students, who were prospective religious clergy freshmen, were not familiar with that language (Boylan & White, 1987). Colleges in the 1700s realized that there were advantages economically to accepting students who were able to pay tuition, but did not meet academic standards or requirements (Arendale, 2010). It was thought that by accepting these students that it would address enrollment and revenue issues and thus resulting in a healthy college budget (McCarville Kerber, 2017). The introduction to an assistance learning program took place during phase 2 (Arendale, 2010). It was established in the mid-1800s that there was insufficient primary education and poor secondary education and there was a need for remediation for students (McCarville Kerber, 2017). The Department of Preparatory Studies was created in 1849 at the University of Wisconsin which provided aid to privileged white male students, including aid in mathematics (Arendale, 2010). Eighty-eight percent of the students enrolled at the University of Wisconsin enrolled in at least one developmental course (Arendale, 2010). The Morrill Acts of 1862 after the Civil War by President Abraham Lincoln motivated the United States to help make postsecondary education available to all people (Davis, 2014).

Phase 3 was when developmental classes were offered in the college preparatory programs (Abraham, 2014). Harvard was the first college to offer a remedial English course for first-year students in 1874 (McCarville Kerber, 2017). Developmental classes were integrated within the institution in phase 4 (Abraham, 2014). A major historical event relating to developmental education is the enactment of the GI Bill. Congress enacted the GI Bill in 1944 which helped more than 8 million veterans who fought in World War II gain an education between 1945 and 1956 (“The GI Bill,” n.d.). Also known as the Servicemen’s’ Readjustment Act, the GI Bill provided veterans with tuition and living stipends for college so that veterans can gain an education, a year of unemployment pay, and loans to pay for homes, businesses, or farms (“The GI Bill,” n.d.). Despite the skepticism the bill had since education wasn’t viewed as the solution for mass unemployment, the veterans who took advantage of the opportunity made on average 10 to 15 thousand more dollars per year compared to those who didn’t take advantage of the bill (“The GI Bill,” n.d.). Institutions’ curriculum was expanded to include career paths due to the GI Bill and those areas included science, business, and engineering (“The GI Bill,” n.d.). The anti-segregation policies of the Civil Rights Movement in the 1960s created a pathway for racial and ethnic minority groups to gain a postsecondary education (“Evolution of Developmental Education,” n.d.). The Civil Rights Act of 1964 also encouraged the United States to make postsecondary education available to more people (Davis, 2014). Phase 5 began more of the developmental education and learning assistance centers besides tutoring alone and was the start of serving general and non-traditional students (Abraham, 2014). As institutions implement open enrollment to all people, there is emphasis on assisting those students who enroll into college requiring additional instruction in order to improve their basic skills (Zachry & Schneider, 2012).

Importance of Developmental Mathematics

The theoretical framework of developmental education resides in developmental psychology and learning theory and was defined as "a comprehensive process which focuses on the intellectual, social, and affective growth and development of all learners at all levels" (Davis, 2014). Developmental mathematics courses were made to improve students' mathematical skills and increase knowledge for those students who lack in that area. Duranczyk and Higbee established in their study that developmental mathematics is beneficial for students at both 2 year and 4 year institutions (2006). They argue there are 4 critical issues that imply the need for developmental mathematics education and those are: educational disadvantages at the elementary to secondary education levels, variations in mathematics standards, tracking, and affective barriers to mathematical achievement (Duranczyk & Higbee, 2006). They further argue that there is a need for developmental mathematics at all levels of postsecondary education (Duranczyk & Higbee, 2006).

Wolfe (2012) created a model in her study to predict success in students' first college level mathematics course and whether students took a developmental mathematics course was a good predictor. She found that developmental students persisted from the fall semester to the spring semester at a lower rate compared to non-developmental students, however, developmental status was slightly significant and did not have a large effect on student success in their first college level mathematics course (Wolfe, 2012). Johnson and Kuennen did a study that analyzed the difference between the performance of students in introductory microeconomics who put off taking developmental mathematics and those who didn't put it off. Introductory microeconomics was the course chosen to analyze because they found research that linked student performance in that course with their mathematics skills (2004). One study they found to support this was by Ballard and Johnson in 2003. It was found in Johnson and

Kuennen's study that students who did take a developmental mathematics course outperformed the students who procrastinated in taking the developmental mathematics course. They say that developmental mathematics not only helps with students' mathematics skills, but also improves their problem solving abilities. They recommend based on their study for students to take a developmental mathematics course their first semester of college (2004). Boatman found that students that took developmental mathematics tended to persist from the first semester to the second semester, however, students' persistence tended to vanish by the second year (Boatman, 2012).

Supporters for developmental education say that it can benefit students from taking developmental mathematics, especially those "marginalized populations" (Brasiel, 2017). Boatman says that students who have taken a developmental mathematics course have a higher retention rate at both 2-year and 4-year institutions compared to students who did not take developmental mathematics (2012). Boatman claims that making postsecondary remediation successful is very important considering the number of students entering college that require remediation (Boatman & Long, 2018). However, there are people who do not support developmental courses. Quarles and Davis (2017) found in their study that the fact that students took a developmental mathematics course was not predictive of certificate or degree completion in college. Traditional remediation mainly instructs students on procedural mathematics skills and those procedural skills are not correlated to completing college level mathematics which is required for degree completion for majority of students (Quarles & Davis, 2017). Students would have to retain an amount of content in one course that is equivalent to one year in middle school or high school (Brasiel, 2017). Remedial mathematics courses would take more time and money for the students who had to take additional coursework that didn't contribute to their degree (Brasiel, 2017). This could be the reason why so many students don't complete their degree (Brasiel, 2017).

High Costs and Risk of Dropping Out

It has been argued that developmental mathematics can be a barrier to students completing college and obtaining a degree (Bonham & Boylan, 2011; Quarles & Davis, 2017). Students who do not complete the remedial math sequence are more likely to leave community college without a credential or without transferring to a 4-year institution (Bahr, 2013). As students are required to complete developmental courses their frustration increases and financial burden increases and thus affects their enrollment (Abraham, 2014). Researchers believe that students become discouraged and their confidence in themselves decreases when they are required to take developmental courses, resulting in students becoming frustrated and dropping out of college (Rosenthal & Wilson, 2003; Deil-Amen & Rosenbaum, 2002). Since students are spending more time and money on developmental courses, this may result in students accumulating more debt than originally anticipated and may affect their financial aid eligibility (Bailey, 2009). Reports of different states cite expenditures in the tens or hundreds of millions of dollars spent annually on developmental services (Bailey, 2009). It was found that the cost of remediation nationwide was 3.6 billion dollars for the 2007 and 2008 school year (Bettinger et al., 2013).

McKinney et al. (2016) conducted a study at the Urban Community College in Texas and one of their research questions asked what the characteristics were of developmental students who took out loans and dropped out of college. They found that 63% of developmental students took out federal loans at a community college and did not earn a certificate or degree or transfer to a 4-year institution (McKinney et al., 2016). Developmental students who were enrolled as part-time students, first generation college students, and obtained a GED were overrepresented among those who dropped out (McKinney et al., 2016). By these students dropping out without a certificate or degree puts them at risk of struggling to make loan payments (McKinney et al., 2016). Enrollment outcomes of students who took out loans and enrollment outcomes of students who did not take out loans were compared in their study as well. They found that developmental students who took out loans had lower observed rate of success compared to developmental students who did not take out loans (McKinney et al., 2016). It was also found that a higher proportion of non-developmental students achieved each of the enrollment outcomes compared to developmental students (McKinney et al., 2016). Students having to take developmental courses can cost them not only financially, but also psychologically (Bailey, 2009). The way students adjust to college life socially can alter their college enrollment and possibly determine if they drop out from college (Tinto, 1975).

Social Integration in Tinto's Theory of Student Retention

Tinto states in his Theory of Student Retention that social integration into the college community is also important and could help determine if a student drops out (1975). As mentioned before, this study will not analyze factors pertaining to the social integration of Tinto's model, but it will be addressed in this literature review. Social integration occurs through connections with fellow college students, connections with people in extracurricular activities, and connections with college faculty (Tinto, 1975). Successful communication and relationships are viewed as important and valuable to students' college experience and can contribute to their likelihood to remain enrolled in college (Tinto, 1975). Academic integration relates to students' goal commitments while social integration relates to students' institutional commitments (Tinto, 1975). The increase of institutional commitment is expected to decrease the chances of students dropping out of college (Tinto, 1987). Social integration might be slightly different for those students who take developmental mathematics since their experience will not be exactly like students who did not have to take developmental mathematics (Umoh, 1994).

Pascarella and Terenzini analyzed the validity of Tinto's Retention Theory and they found that social integration had a larger impact on female students than male students (1983). Terezini and Wright conducted a study that followed a group of students for 4 years to analyze their academic and social integration each year and found that the amount of integration there was in a year affected the following year (1987). Academic and social integration was the focus of the study conducted by Ishitani and it was found that social integration didn't show any statistical significance in the persistence of first-year students (2016). It has been suggested that emotional and social health of students has an impact on their college success (Pritchard & Wilson, 2003). The purpose of Pritchard and Wilson's study was to analyze the social and emotional factors of college students and if those affected their GPA or retention rates. The results of their study show that both factors had an impact on students' GPA and retention rates (2003).

The goal of Aydin's study was to investigate personal factors and if those personal factors were predictors of student success (2017). Aydin says that students' communication with classmates and faculty has a great influence on emotional functioning and on student achievement (2017). Instructors being responsive to students can have a positive effect on students' achievement along with students' relationships with fellow classmates (Aydin, 2017). Students who are relaxed and make good connections show higher academic achievement (Aydin, 2017). It was found in Aydin's study that classroom communication was statistically significant in predicting student success and is a factor that can alter student success (Aydin, 2017).

Alharthi also says that the failure for a first-year student to make friends can lead to that student dropping out of their studies (2020). Universities have made an effort to help students in their transition into college by developing First-Year Student programs or courses (Alharthi, 2020). A qualitative study was conducted to analyze the My Uni-Buddy program at a university to see if students benefited from the program (Alharthi, 2020). The Uni-Buddy program was created to help first year students to make connections and quickly adjust to their new college life and it was found that students greatly benefited from the program (Alharthi, 2020). Not only socially, but also the way students adjust to college life academically is also important and can contribute to a student's decision to drop out of college (Tinto, 1975).

Potential Student, Instructor, and Classroom Predictors

Potential Student Predictors

Differences in achievement in mathematics and attitudes toward mathematics between males and females have been a hot debate for many years (Leder, 2010). There are studies that show gender to be a significant predictor in developmental mathematics. The goal of Kristen Fong's quantitative study was to create a model showing successful progression in developmental education based on different factors, such as student and institutional and developmental math factors, by using logistic regression. She found that female students have better odds of progressing at every stage of developmental mathematics compared to male students (2015). In a quasiexperimental study by Spradlin and Ackerman, gender performance differences in mathematics were analyzed and found a significant difference between posttest scores of males and females (2010). Females performed better than males in both traditional instruction and traditional instruction with computer-assisted instruction (Spradlin & Ackerman, 2010). Wolfe's dissertation had the goal to create a model to predict success in students' first college level mathematics courses and to predict the persistence of students from fall semester 2006 to spring semester 2007. She found gender to be a significant predictor of persistence in her study. It was also found that females had a greater chance of succeeding in their first college-level mathematics (2014). A dissertation by Hunt had the goal of analyzing different predictors of student success in two developmental mathematics courses, Elementary Algebra and Intermediate Algebra, at Marshall University and found gender to be statistically significant for Intermediate Algebra. She analyzed variables that potentially predicted success on the final exam of each course and the overall grade of each course (2011).

There are also studies that show gender to be a non-significant predictor. A quantitative study conducted by Taylor analyzed the difference between web-based or computer assisted curriculum in remedial mathematics. She addressed other variables in her study, including gender, and found that there were no differences in achievement between males and females in developmental mathematics (2006). Martinez created a model in his quantitative study to predict success in developmental mathematics at Premier Technical University so that administrators would be able to make any improvements in order to help their students succeed. He found gender to be a non-significant predictor of success (2017). Gender was found to be significant for Intermediate Algebra in Hunt's dissertation, however, gender was not significant for the other developmental mathematics course in her study, Elementary Algebra (2011). Millea was concerned about retention rates and student success and analyzed different predictors of student success in college. She found that there were no differences in retention rates between males and females (2018). Tinto's Model of Institutional Departure was the framework for the study by Umoh that analyzed the relationship between a 2-year developmental mathematics course and variables found through retention research. Gender was included as one of the variables in the study and no statistical significance was found (1994).

Age is categorized as traditional and non-traditional. Traditional is considered between 17 to 22 years old while non-traditional is considered 24 years or over (Wolfe, 2012). A non-traditionally aged person is less likely to attempt enrolling in a course, but if they do enroll then the odds of passing a course increases (Fong, 2015). Additionally, for each additional year of student age the probability of retention for first year students increases 0.6% (Millea, 2018). Ran's study analyzed the difference between part-time and full-time faculty and if that had an impact on student success. A study by Wolfe used a sample of students from 23 community colleges in Virginia and examined the persistence of students to fall 2007 and student success in their first college-level mathematics course. Whether a student took developmental mathematics was the main predictor of the study, but age was included as a variable and was found to moderate both success in their first college-level mathematics and persistence (2012). Developmental courses were found to be more beneficial for traditionally aged students and non-traditionally aged students tended to persist if they have taken a developmental mathematics course (Wolfe, 2012).

Age was included as a predictor in Martinez's study and found age to be non-significant in predicting success in developmental mathematics (2017). It was found in Millea's study that for each additional year of a student's age reduced the probability of obtaining a degree by 1.9%. She argues that this could be due to students not graduating with their degrees within 6 years of initial enrollment (2018). The goal of Taylor's study was to investigate the effects of Assessment and Learning in Knowledge Spaces (ALEKS) on Intermediate Algebra which is a developmental or remedial mathematics course. There were no differences in mathematical achievement that were found in age in this study (2006). In Umoh's research, students' ages ranged from 18 to 45 years old and no statistical significance was found in the variable age (1994). A negative relation between traditionally aged students and persistence from fall semester to fall semester was found in Wolfe's dissertation (2012).

Referring back to the study by Kristen Fong, she found that it is less likely for African American students to progress through the levels of developmental mathematics compared to White students. She also found that there are higher odds of Latino students attempting each level of mathematics compared to White students, but Latino students have lower odds of passing each level (2015). African Americans were found to persist from the fall semester to the spring semester at lower rates compared to other minority groups which persisted at a higher rate (Wolfe, 2012). It was also found in the same study that African Americans had lower chances of succeeding in college level courses (Wolfe, 2014). A quantitative study by Wheeler analyzed the relationship between student success and graduation and demographic variables. The study found that gender, race and developmental math status was related to college-level mathematics outcomes and graduation outcomes (2017).

There also exists literature that supports race being a non-significant predictor of student success. Martinez included ethnicity in his model predicting success in remedial mathematics and found all categories used in his study, which are White, African American, and Hispanic, to be non-significant predictors (2017). Ethnicity was found to not affect student achievement in mathematics (Taylor, 2006). Recalling Millea's research on student achievement and college retention and graduation, race was included as a variable and was found to be non-influential on college retention or graduation rates (2018).

ACT math score was found to be a significant predictor of success in both elementary algebra and intermediate algebra in Hunt's dissertation (2011). One of the research questions asked by Stephens asked if there existed a relationship between ACT math score and students' overall grades in three different mathematics courses, which two of the courses were developmental courses. The two developmental mathematics courses were elementary algebra and intermediate algebra. ACT math score was non-significant for the elementary algebra course in his study, however, the intermediate algebra course and the non-developmental mathematics course was significant (2005).

Stephens had a similar question for ACT reading score as he did for ACT math score. The research question asked if there was a relationship between ACT reading score and students' overall grade in the same three mathematics courses. Similar to his previous findings for ACT math score, he found ACT reading score to be non-significant for the elementary algebra course, but the intermediate algebra and the non-developmental course was significant. Stephens concluded that higher ACT reading scores are related to better student grades in the mathematics courses (2005).

Pretests are given to students at the beginning of a class in order to evaluate their knowledge before any instruction. A similar test, a posttest, is given at the end of the course to evaluate the knowledge students gained in the course. Hunt used pretests as a predictor variable in her study and found that the inhouse-developed math pretest was the strongest predictor of student success in developmental mathematics (2011). Spradlin's quasi-experimental study used a nonrandomized control group pretest-posttest design in order to compare student developmental mathematics performance in a traditional structured course and traditional instruction with computer-assistance structured course. She found in her ANCOVA analysis that pretest was significant (2010). Contradicting their findings, Hutson in 1999 found that math pretest was a non-significant predictor of student success in developmental mathematics. For students in Stephen's study, high school GPA was found to be a good predictor of student success in elementary algebra, intermediate algebra, and a non-developmental mathematics course (2005).

Socioeconomic status (SES) is often measured in combination of education, income, and career, is the social status or class of a person or group (Socioeconomic Status, 2020). Fong's results indicated that full-time students with financial aid have higher odds of persisting through all the levels of developmental mathematics compared to students who were part-time and did not obtain financial aid (2015). Martinez included source of tuition, categorized as loans, grants, scholarships, and other, in his developmental mathematics predictor model and found all sources to be non-significant predictors of success (2017). Ran's study compared part-time faculty and full-time faculty's impact on student success and Pell grant eligibility was included as a variable and was found to be a significant predictor of student success in developmental courses which included developmental mathematics (2019).

First generation college students are those students whose parents do not have a college degree. A study conducted by Guerrero et al. attempted to fill any gaps in research relating to how effective Mathematics Emporium models address students' needs which Mathematics Emporia is learning environments that are technology supported (2020). Students' needs were based on gender, race, international status, and first generation status versus non-first generation status. Out of the courses examined, MAT 100 (Mathematical Pathways) and MAT 110 (Algebra for Precalculus) did not satisfy any degree requirements and were terminal courses for many students (Guerrero et al., 2020). It was found that first generation status versus non-first generation pass rate was statistically significant for MAT 110 and that first generation students were 5% to 7% less likely to pass compared to non-first generation students (Guerrero et al., 2020).

Students whose parents have no college experience are not as likely to attend college compared to their peers (Engle, 2007). If they do enroll in college, it is more likely to be a 2 year institution than a 4 year institution (Engle, 2007). First generation college students are more likely to be non-traditionally aged, female, African American or Hispanic, have dependent children, and come from low-income households which are associated with lower rates of college attendance and successful completion of a degree (Engle, 2007). Also, many first generation college students struggle to adapt to college life (Quinn, 2019). These students are also more likely to withdraw from courses or repeat courses they've previously attempted (Chen, 2005). First generation students are less likely to obtain a degree and persist to graduate (Chen, 2005; Engle, 2007). Since they are not as likely to earn a 4 year degree, they are underrepresented among graduate degrees and are unlikely to pursue a graduate degree (Engle &

Tinto, 2008). First generation college students are often considered at risk in retention and academic persistence (Hand & Payne, 2008).

First generation students who were participants of a study conducted by Hand and Payne were from an Appalachian university in the Student Support Services program which analyzes factors that could contribute to academic persistence of students (2008). They found that family, finances, relationships, internal locus of control, emotional support, and communication of information were all important factors that contributed to academic persistence (Hand & Payne, 2008). However, the students that were interviewed in their study showed no indication of being at a disadvantage compared to students whose parents had college experience (Hand & Payne, 2008).

First generation and low income students were not likely to choose mathematics as a major and stay in that major (Engle & Tinto, 2008). First generation college students are underrepresented in PEMC (physical sciences, engineering, mathematics, and computer science) and STEM (science, technology, engineering, and mathematics) fields and are more likely to leave those degree programs compared to their peers who are not first generation students (Dika & D'Amico, 2016). Dika and D'Amico stated in their conclusion that grades of first generation students in any major, including PEMC and STEM majors, in their first semester mattered when predicting if those students would return for a second year (2016).

Engle and Tinto did an analysis of NPSAS (National Postsecondary Student Aid Study) data and found that there is more of a chance for first generation students to take developmental courses compared to students who are not first generation status (2008). The NPSAS analyzes how people pay for postsecondary education (Engle & Tinto, 2008). Fifty five percent of first generation students were required to take developmental courses while only 27% of students whose parents obtained a degree had to take developmental courses (Chen, 2005). Chen reported that 40% of first generation students took developmental mathematics courses (2005). Developmental instructors are likely to have many first generation students in their courses due to low ACT or SAT scores or low grades in high school (Quinn, 2019; Hand & Payne, 2008).

Potential Instructor Predictors

The instructor gender was found to be statistically significant when analyzing predictors of success in elementary algebra (Hunt, 2011). Instructor gender could not explain any negative effects of part-time employment status on student outcomes (Ran, 2019). Instructor degree is categorized as bachelors, masters, and doctorate in this study. In Ran's study comparing part-time and full-time faculty, the degree the instructor possesses could not explain any effects that part-time instructors have on student success (2019). Employment status refers to full-time faculty, part-time faculty, or graduate student status. Statistical significance was found in full-time faculty status in students attempting elementary algebra, but not necessarily passing elementary algebra (Fong, 2015). Hunt found that instructor employment status was a good predictor of student success in elementary algebra, but graduate student status was not included in her study (2011). Students who were enrolled in a developmental mathematics course with a part-time instructor tended to have good outcomes, however, they were not likely to pass the second course when taught by a full-time instructor (Fong, 2015). Student persistence and success in developmental mathematics taught by part-time instructors were no different compared to full-time instructors, however, there was less of a chance for students to enroll in and pass their gateway course if their developmental mathematics instructor was part-time (Ran, 2019). Ran also found that focusing on faculty professional experiences at six colleges that part-time faculty have less institutional knowledge compared to full-time faculty, but it did not affect student success rates (2019).

Potential Classroom Predictors

It was found that for each additional student enrolled in a developmental mathematics course that the odds of students being successful and passing decreased and smaller class sizes were associated with greater chance of success (Fong, 2015). However, Little reported that class size was not a significant predictor of developmental mathematics with a minimum class size of 19 students and a maximum class size of 50 students (2002). In Fike's study, he found that students who had an Intermediate Algebra course once a week for 150 minutes did better overall compared to those students in the same course that had a class meeting twice a week for 75 minutes. He concluded that the number of class meetings per week was a significant predictor of success in developmental mathematics (2005). Time of day and number of class meetings per week were statistically significant in predicting student final grade in Elementary Algebra (Hunt, 2011).

Summary

Several students enter post-secondary education lacking the basic mathematical skills. History shows that institutions saw advantages to accepting these students and created developmental mathematics with the goal of helping students succeed in their college career. Literature shows the importance of developmental mathematics, but there are also opposing views of developmental mathematics. Although developmental mathematics are important, there are still concerns relating to low rates of success for these students thus leading to students spending more time and money and having to take out student loans and not being able to pay them back. Students' adjustments socially to the college community are also important and can affect their college success and can lead to students' decision to drop out from college (Tinto, 1975). The academic integration of students is the primary focus of this study and these predictors could possibly contribute to students' college success and the decision to drop out of college (Tinto, 1975). All of this information has been reviewed and there is now an overall review of where developmental mathematics came from and why developmental students take developmental courses and how these developmental courses can affect students and what can potentially affect these students' college success.

CHAPTER III: METHODOLOGY

The purpose of this study is to reveal areas of possible improvement to developmental mathematics courses by examining potential predictors of success. A developmental mathematics course at Shawnee State University will be examined and participants include students who were previously enrolled in the course. Regression and ANOVA techniques will be implemented for analyses. This research design is ex-post facto, so data for this study already existed and needed to be collected according to the purposes of this study. This chapter will present the overall methodology that will be applied to this study.

Setting and Participants

The participants for this study consist of 348 students previously enrolled in a developmental mathematics course, Math 0101: Basic Algebra with Geometry and Applications. The Shawnee State University Course Catalog describes this developmental mathematics course as a course for students with a "good background in arithmetic, but little or no background in algebra and geometry. Topics include linear expressions and equations in numeric, graphic, and symbolic form; solving linear equations and inequalities; linear models; operations with exponents; scientific notation; roots, radicals, and fractional exponents; radical equations; polynomial expressions" (2020). The semester enrollment dates of students ranged from spring 2017 to fall 2019, also including summer semesters, giving a total of 8 semesters (Spring 2017, Summer 2017, Fall 2017, Summer 2018, Fall 2018, Spring 2019, Summer 2019, and Fall 2019).

Data from the year 2020 was not included in this study due to the effects of the Covid-19 global pandemic. Exams during this time were given as online exams with pooled questions that were not proctored while the exams before the pandemic were given in a face-to-face setting and with paper and pencil. For the purposes of this study, data from 2020 during the pandemic was excluded. However, this might be something to explore in another study. Shawnee State University is a public university located in Portsmouth, Ohio which is in the Appalachian region. Students might be more representative to the Appalachian region and so careful consideration should take place before generalizing to students in urban areas. Generalizability consideration also needs to take place with students located at private colleges and universities in other states. Undergraduate enrollment at Shawnee State University is approximately 3,600 and so consideration should be taken when generalizing to larger universities with larger undergraduate enrollment.

According to Andy Field et al. (2012, p. 58), with a standard alpha level of .05 and a power of .80, a sample size of 783 would be adequate for a small effect size, a sample size of 85 for a medium effect size, and a sample size of 28 for a large effect size. Field et al. (2012, p. 59) referred to Cohen and found that Cohen's Standard Effect Sizes are .10 being a small effect size, .30 being a medium effect size, and .50 being a large effect size. Regression techniques will be used in this study and there are many rules of thumb as far as what would be considered an adequate sample size for regression (Field et al., 2012). Field states that the two most common rules are 10 cases per predictor and 15 cases per predictor (Field et al., 2012, p. 273). With this study there are 15 predictors, so the sample size according to the 10 cases per predictor rule should be at least 150. For the 15 cases per predictor rule, the sample size for this study should be 225. Based on the book by Field et al. (2012), a sample size of 348 for this study meets the requirements for a medium to large effect size.

Further, a power analysis was conducted to also ensure the sample size is acceptable. Regression and ANOVA will be the techniques that will be implemented according to the research questions. A priori power analysis was conducted for multiple regression using G*Power using standard alpha level of .05, power of .80, and a medium effect size indicated by G*Power to be .15. According to the results from a power analysis using G*Power, adequate sample size should be at least 139. The sample size for this study exceeds that amount and ensures that the sample size obtained for this study is acceptable.

Instrumentation

The composite score for the pretest was used in this study rather than the individual questions. Five different versions of the pretest were created by the Director of Developmental Mathematics at Shawnee State University and were made to correspond to the Math 0101 course description and objectives. The course objectives are listed in Appendix C. The versions of the pretest that were given in the semesters of this study can be found in Appendix D. Before students were given the pretest, they were told that a similar test at the end of the course will be given to them. The posttest given at the end of the course served as the final exam. Additionally, students were told that the pretest would not be averaged into their final grades. To motivate students to do their best on the pretest, they were told that their pretest will count as extra credit. The type of questions of each pretest can be found in Appendix E. During the pretest, students were allowed to use a modified version of the Wisconsin Mathematics Formula Reference Sheet (Appendix B). Examples of questions on the pretest can be found in Appendix F. The departmentally-developed pretest satisfies the validity requirement since it was created by the Director of Developmental Mathematics, who has significant experience teaching Math 0101 and other developmental mathematics courses. Additionally, full-time developmental mathematics instructors reviewed and provided feedback on the exams.

Procedure

The following student data was obtained from student records: gender, age, race, ACT Math score, ACT Reading score, 1st generation status, Socioeconomic Status, and high school GPA. The composite pretest scores were kept by Shawnee State University's Director of Developmental Mathematics. Instructors' gender, degree, and employment status were collected from department records. Class size, number of times a class meets per week, and the time of day the class met was collected from class schedules. Prior to data collection, the researcher received IRB approval to conduct this study. The approval can be found in Appendix A. All identifiers have been removed before the data was released to the researcher.

Analysis and Data Processing

Once the researcher receives the data set, the data will be organized, cleansed, deleted, and recoded as necessary. Data will be coded as shown in Table 1 and Table 2. Some categorical variables have more than two categories, such as race or ethnicity, and require dummy coding, which is a way of representing multiple categories when implementing regression techniques. (Field et al., 2012, p. 303). Variables requiring dummy coding are also indicated in Table 4. Cases with missing values will be dealt with casewise.

Table 1: Independent Variables (Predictors)

Predictor	**Category**	**Coded as**
Gender	Student	1 = male 0 = female
ACT Math Score	Student	Numerical
ACT Reading Score	Student	Numerical
Race	Student	Recoded using dummy coding
Age	Student	Traditional (17 to 22 years old) = 1 Non-Traditional (23 years old and up) = 0
Socioeconomic Status (determined by Pell Grant status)	Student	1 = Pell Grant 0 = No Pell Grant
First Generation Status	Student	1 = Yes 0 = No

High School GPA	Student	Numerical
Pretest Score	Student	Numerical
Gender	Instructor	1 = male 0 = female
Employment Status	Instructor	Recoded using dummy coding
Degree	Instructor	Recoded using dummy coding
Class Time of Day	Classroom	Recoded using dummy coding
Class Size	Classroom	Numerical
Number of Meetings per Week	Classroom	3 times a week = 1 2 times a week = 0

Table 2: Dependent Variables (Outcomes)

Variable	**Coded as**
Final Exam	Numerical
Final Overall Grade	1 = Pass 0 = Fail

Correlations will examine the relationship between variables, while regression techniques will be used for predictions (Field et al., 2012, p. 246). By using these regression analyses, predictors will be examined to determine if they make a significant contribution to predicting an outcome (Field et al., 2012, p. 253). These research questions will require different types of regression analyses which will be described. R statistical software will be used in running all tests and analyses (R Core Team, 2020).

- Research Question 1: Are student, instructor, and/or classroom characteristics predictive of success in developmental math courses?

Student characteristics include gender, age, race, ACT Math score, ACT Reading score, math pretest score, 1st generation status, Socioeconomic Status (SES), and high school GPA. Instructor characteristics include gender, degree, and employment status. Classroom characteristics include class size, number of times a class meets per week, and time of day the class meets. The final grade in the course is categorized as pass or fail where pass is a C or higher and fail is lower than a C. Due to the dependent variable having two categorical outcomes, forward selections logistic regression has to be implemented which will predict the probability of an event occurring for a case (Field et al., 2012, p. 313-315). Interpretation of logistic regression is the value of the odds ratio which is an indicator of change in the odds resulting from change in the predictor by one unit (Field et al., 2012, p. 319). Before creating any models, the following assumptions must be checked: linearity, independence, and no multicollinearity (Field et al., 2012, p.321-322). In regular regression, both linearity (outcome and predictors have linear relationship) and independence (cases of data are not related) are assumed (Field et al., 2012, p. 321). Multicollinearity pertains to the predictors being highly correlated which can be problematic (Field et al., 2012, p. 322). Appropriate subtests to analyze individual predictors must also be conducted. Once these assumptions are tested and subtests are done, the forward selections logistic regression analysis will be conducted. Hunt, Fong, and Martinez used similar techniques in their studies to identify predictors of success in developmental mathematics (2011; 2015; 2017).

- Research Question 2: Are student, instructor, and/or classroom characteristics predictive of final exam score?

Forward selection multiple regression will be needed for this research question because of testing multiple predictors to see if any are statistically significant. The basic principles of simple linear regression apply to multiple regression except there is more than one predictor (Field et al., 2012, p. 261). According to Field et al., the following assumptions should be checked in any regression analysis: linearity, independence, multicollinearity, homogeneity of variances, non-zero variance, normality, and independent and normally distributed errors (2012,

p. 271-272). Once assumptions are tested and appropriate subtests as mentioned previously are conducted, then the multiple regression analysis will be conducted. Hunt and Stephens used similar techniques in their studies with the goal of identifying predictors of success in developmental mathematics (2011; 2005).

- Research Question 3: Is the student predictor Race X SES a significant predictor of success in a developmental mathematics course when controlling for high school GPA?
- Research Question 4: Is the student predictor Race X Gender a significant predictor of success in a developmental mathematics course when controlling for high school GPA?
- Research Question 5: Is the student predictor SES X First Generation Status a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

Interactions between particular student predictors will be tested for research questions 3, 4, and 5. Based on information found in the literature review, these interactions will be further explored. Fong (2015) found that females have better odds of progressing at every stage of developmental mathematics compared to male students. In the same study by Fong (2015), it was found the African American and Latino students were less likely to progress through the levels of developmental mathematics courses or passing at each level. Fong also indicated that students who received financial aid and who were full time were more likely to persist through the different levels of developmental mathematics (2015). According to Engle (2007), first generation college students are more likely to be female, African American or Hispanic, and come from low-income households which are associated with low college attendance rates and completion of a degree. Guerrero et al. (2020) found that first generation students were 5% to 7% less likely to pass the non-credit mathematics courses analyzed in their study. These findings motivated the addition of the research questions focused on these interactions. The statistical techniques will be similar to the techniques that will be used for research questions 1 and 2.

Summary

The goal of this study is to reveal areas of potential improvement to developmental mathematics courses by examining student, instructor, and classroom characteristics in a developmental mathematics course at Shawnee State University. The sample for this study consists of students who were enrolled in Math 0101 between the spring semester of 2017 to fall semester of 2019. The data was collected from existing sources such as student and department records. The sample size for this study is 348 and is acceptable according to the book by Field et al. (2012) and a power analysis that was conducted. Appropriate regression and ANOVA statistical techniques were chosen for the research questions. Assumptions for each statistical technique must be tested and subtests must be conducted to examine individual predictors. Once the tests and analyses are conducted, the results will be presented.

CHAPTER IV: RESULTS

The results of this study will be presented in this chapter. The purpose of this study is to examine potential predictors of success with the goal of exposing areas of possible improvement to developmental mathematics courses. Regression and ANOVA techniques were used in the analyses of this study. The descriptive statistics will be reviewed along with the results from the subtests for each predictor and the tests for the assumptions. Each of the research questions was analyzed and the results for each question will be presented. The research questions for this study are:

- Research Question 1: Are student, instructor, and/or classroom characteristics predictive of success in developmental math courses?

- Research Question 2: Are student, instructor, and/or classroom characteristics predictive of final exam score?

- Research Question 3: Is the student predictor Race X SES a significant predictor of success in a developmental mathematics course when controlling for high school GPA?
- Research Question 4: Is the student predictor Race X Gender a significant predictor of success in a developmental mathematics course when controlling for high school GPA?
- Research Question 5: Is the student predictor SES X First Generation Status a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

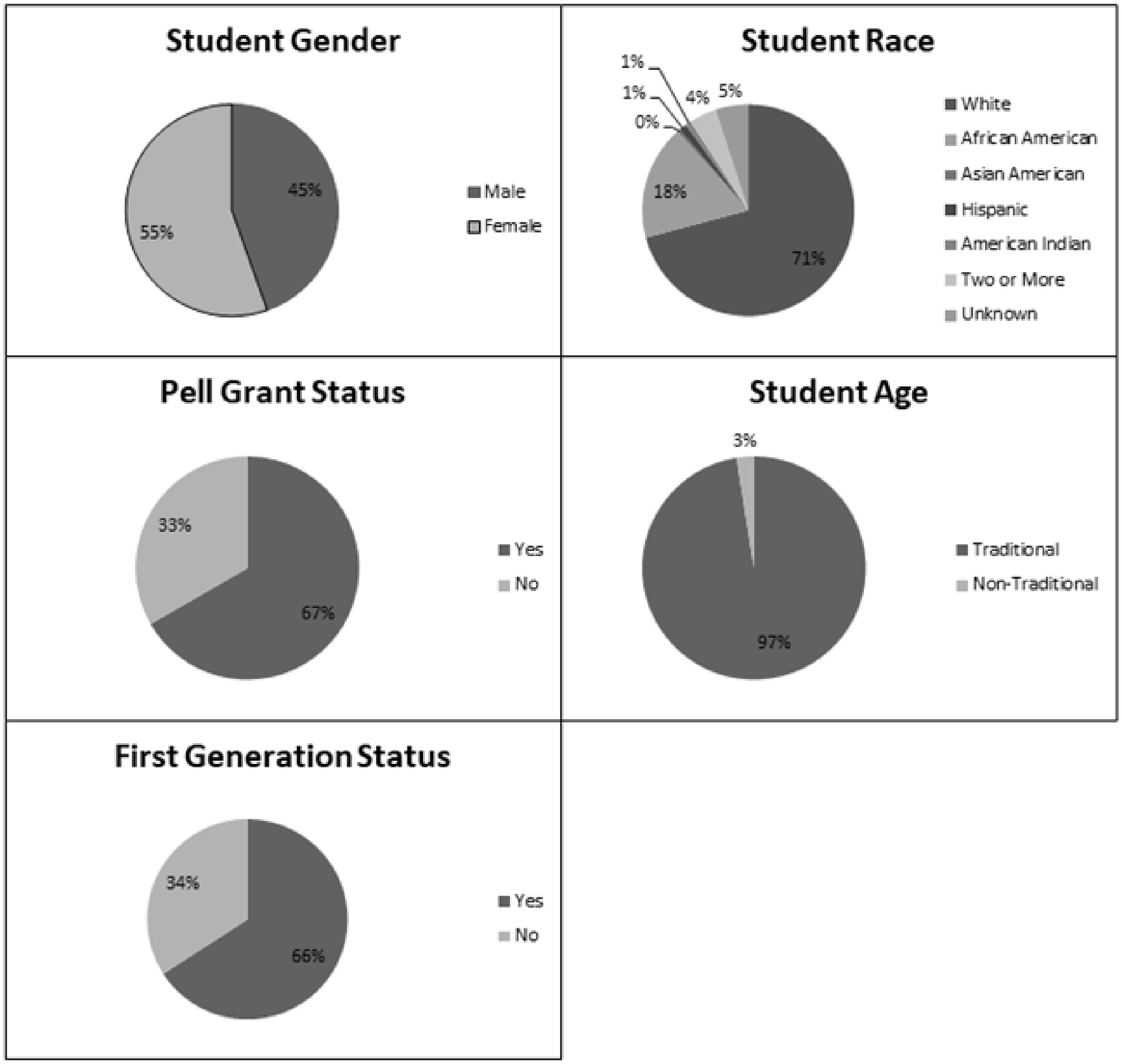
Data Cleansing

Once the researcher received the data set, the data was examined for missing data values. There were cases with no ACT reading score and no ACT math score. High school GPA is measured numerically in this study, so cases that obtained a GED and did not have a high school GPA were eliminated. There were also cases without a pretest score in the data set. A total of 108 cases were eliminated for those reasons. The initial sample size was 348. The sample size that will be examined is 240.

Description of Study Participants

A total of N = 240 cases were examined in this study with n = 133(55%) being female and n = 107(45%) being male. The breakdown of race of the participants is as follows: White n = 170(71%), African American n = 42(18%), Asian American n = 1(< 1%), Hispanic n = 3(1%), American Indian n = 2(< 1%), Multiracial n = 10(4%), and unknown n = 12(5%). Traditionally aged students are between 17 and 22 years old and non-traditionally aged students are 23 year old or above in this study. Traditionally aged students consist of n = 234(98%) and non-traditionally aged students consist of n = 6(2%) of the sample. Socioeconomic status is determined by Pell Grant eligibility in this study. Students who obtained the Pell Grant consist of n = 160(67%) while students who did not obtain the Pell Grant consist of n = 80(33%). Students who were first generation students consist of n = 158(66%) and students who were not first generation consist n = 82(34%). Figure 2 shows representations of the student categorical variables.

Figure 2: Representations of categorical predictors.



The mean and standard deviation of the quantitative variables will be presented as mean(standard deviation). The descriptive information of the student quantitative variables is presented in Table 3. The mean ACT math score is 15(1.47) while the mean ACT reading score is 17(3.96). The mean high school GPA is 2.83(.61) and the mean pretest score is 41(14.14).

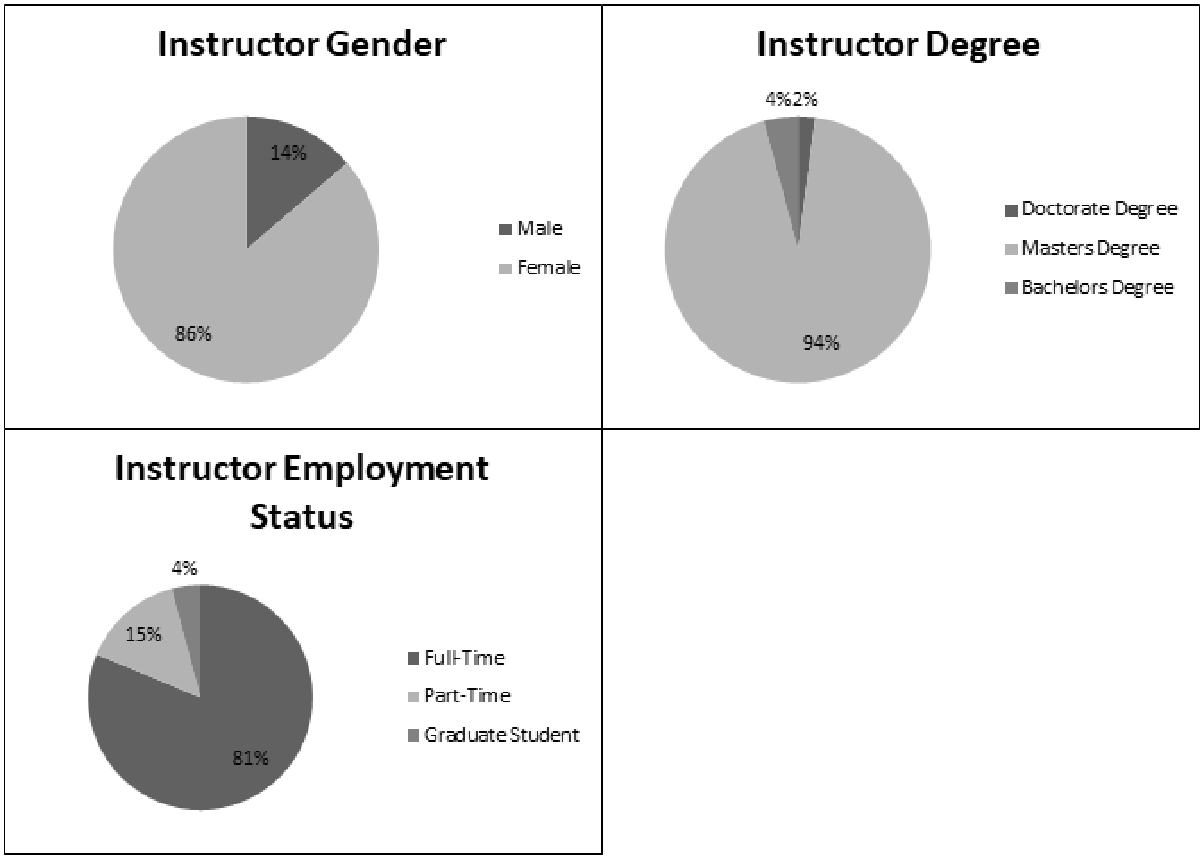
Table 3: Descriptive information of student quantitative variables

Variable	**Mean(SD)**

ACT Math	15(1.47)
ACT Reading	17(3.96)
High School GPA	2.83(.61)
Pretest	41(14.14)

Instructor characteristics include gender, employment status, and degree. There were 6 instructors that taught Math 0101 during the semesters that is being analyzed in this study where 1 was a male and the other 5 were females. Out of the 7 instructors, 1 had a doctorate degree, 1 had a bachelors degree, and the other 4 had a masters degree. One instructor was a graduate student, 2 of the instructors were part-time, and 3 of the instructors were full-time. The number of students that had a female instructor consist of n = 207(86%) and students who had a male instructor consist of n = 33(14%). The number of students who had an instructor with the following employment statuses as follows: full-time n = 195(81%), part-time n = 35(15%), and graduate student n = 10(4%). The number of students who had an instructor with the following degrees as follows: doctorate n = 5(2%), masters n = 225(94%), and bachelors n = 10(4%). Figure 3 shows representations of the instructor predictors.

Figure 3: Representations of Instructor Predictors

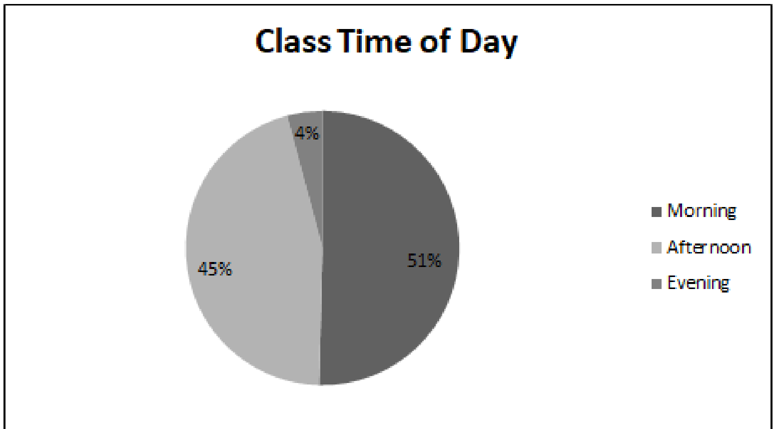


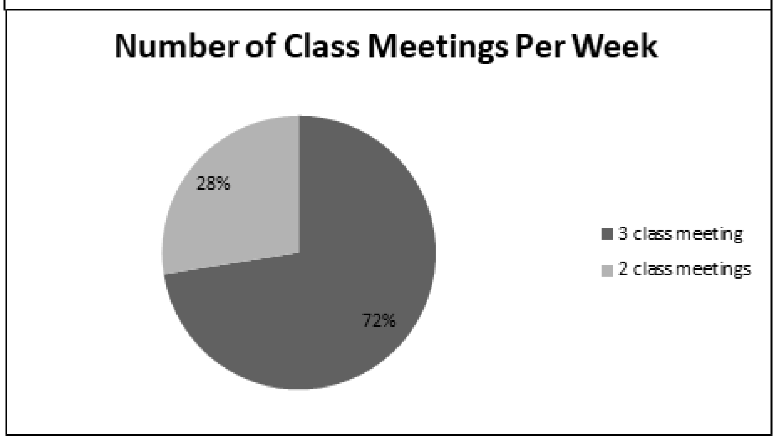
Classroom characteristics are class size, time of day, and number of class meetings per week. The mean class size is 21(5.69). Students who had 3 class meetings per week consist of n = 174(72%) and students who had 2 class meeting consist of n = 66(28%). Classes that were in the morning were n = 121(50%) and classes that were in the afternoon were n = 109(45%). Evening classes consist of n = 10(4%). Table 4 represents the classroom quantitative variables and figure 4 represents classroom time of day and number of class meetings per week.

Table 4: Descriptive information for class size

Variable	**Mean(SD)**
Class Size	21(5.69)

Figure 4: Representations of class time of day and number of class meetings per week



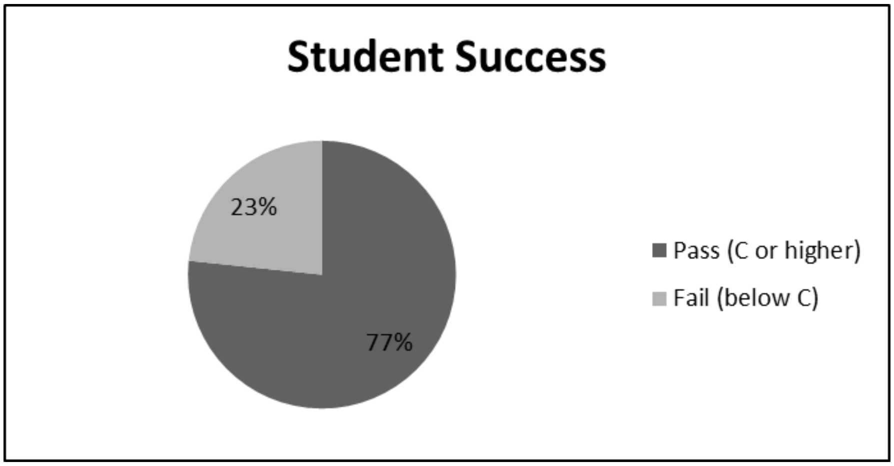


The dependent variables of this study are final exam score and final grade in the course. The mean final exam score is 61(22.16). The final grade in the course is categorized as pass (C or higher) and fail (below C). Students who passed Math 0101 consist of n = 184(77%) while students who did not pass the course consist of n = 56(23%). Table 5 presents the descriptive information of the final exam score and figure 5 shows the representation of student success in Math 0101.

Table 5: Descriptive information of final exam score of students

Variable	**Mean(SD)**
Final Exam Score	61(22.16)

Figure 5: Representation of student success



Subtest Results of Individual Predictors

A subtest needed to be conducted on each predictor and each predictor required a different subtest. Quantitative predictors required independent t-tests and a correlation t-test (Pearson Correlation Analysis). Categorical predictors required independent sample t-tests or an ANOVA and chi-square tests. Instructor characteristics will not be included in the analysis on the research questions due to lack of variation in the categories. Student age will also be excluded due to lack of variation. The predictors that will be examined are student gender, ACT math score, ACT reading score, race, socioeconomic status, first generation status, high school GPA, pretest score, class size, time of day, and number of meetings per week.

Categorical Predictors

The categorical predictors consist of student gender, race, socioeconomic status, first generation status, class time of day, and number of class meetings per week. A chi-square test is required when both the predictors and outcome are categorical. So, a chi-square test examines the two categorical variables (the categorical predictors and success in course) to see if there exists a relationship or if the variables are independent. In order to perform a chi-square test and not violate the assumption that expected cell counts need to be at least 5 some groups had to be combined. For time of day, afternoon and evening cases were combined and labeled as PM. For race, Hispanic, American Indian, Asian, Multiracial , and unknown were combined and labeled as other. Table 6 presents the results from the chi-square tests.

Table 6: Results from chi-square tests examining relationship between categorical predictors and success in the course (pass or fail)

Predictor	**Test-Statistic**	**P-Value**
Student Gender	$\chi(1) = 9.12e\text{-}31$	1
Student Race	$\chi(2) = .66$	.72
Socioeconomic Status	$\chi(1) = .07$	.79
First Generation Status	$\chi(1) = .19$	.66
Class Time of Day	$\chi(1) = 1.70$	.19
Number of Class Meetings per Week	$\chi(1) = 1.96$	.16

An independent sample t-test and ANOVA is required when the independent variable is categorical and the dependent variable is quantitative. Independent sample t-test is used when the independent variable has two categories while an ANOVA is used when there are more than two categories. So, an independent sample t-test or an ANOVA is needed when the dependent variable is final exam score. One of the assumptions of ANOVA is normality and a Shapiro-Wilk normality test was ran to check this. The normality assumption is violated for class time of day and student race, so the Kruskal-Wallis Test (non-parametric test) was conducted for both. For race, the results of the Kruskal-Wallis Test show no significant difference in the final exam score across student race. For time of day, the Kruskal-Wallis Test results show no significant difference in final exam score across class time of day. Table 7 presents the results from the independent sample t-tests and non-parametric ANOVA tests.

Table 7: Results from independent samples t-tests and Non-Parametric ANOVA tests when the dependent variable is final exam score

Predictor	Test	Test-Statistic	P-Value
Student Gender	Independent Samples T-Test	t(224.45) = .36	.72
Student Race	Non- Parametric ANOVA (Kruskal-Wallis Test)	$\chi(6) = 1.69$	.95
Socioeconomic Status	Independent Samples T-Test	t(184.95) = .77	.44
First Generation Status	Independent Samples T-Test	t(153.38) = -0.07	.94
Class Time of Day	Non- Parametric ANOVA (Kruskal-Wallis Test)	$\chi(2) = 1.13$	.57
Number of Class Meetings per Week	Independent Samples T-Test	t(238) = .79	.43

Quantitative Predictors

The quantitative predictors consist of ACT math score, ACT reading score, high school GPA, pretest score, and class size. An independent t-test was conducted to examine the equality of the group means. In other words, is there a mean difference in the quantitative predictor across success in the course (pass or fail)? The independent t-test detected a statistical significance difference in course success across ACT math scores ($t(68.05) = -4.93$, $p < .001$). On average, ACT scores of students who passed the course had a higher mean (mean = 15.72, SD = 1.16, n = 184) compared to the ACT scores of students who failed the course (mean = 14.41, SD = 1.89, n = 56). There was also a statistical significance in the difference in student success across high school GPA ($t(238) = -2.65$, $p < .01$). On average, high school GPA of students who passed the course had a higher mean (mean = 2.88, SD = .59, n = 184) compared to the high school GPA of students who failed the course (mean = 2.64, SD = .62, n = 56). The difference in student success across pretest score was statistically significant as well ($t(238) = -4.18$, $p < .001$). Pretest scores of students who passed the course had a higher mean (mean = 43.05, SD = 13.51, n = 184) compared to the Pretest scores of students who failed the course (mean = 34.32, SD = 14.21, n = 56). Also, the difference in success in course across class size is statistically significant ($t(238) = 2.27$, $p < .05$). On average, the class size of students who passed the course had a lower mean (mean = 20.34, SD = 5.52, n = 184) compared to the class size of students who failed the course (mean = 22.29, SD = 6.01, n = 56). Table 8 presents the results from the independent samples t-tests for the quantitative predictors. A Pearson Correlation Analysis was also conducted to examine the relationship between the quantitative predictors and final exam score. All predictors have a weak relationship and high school GPA is the only predictor with a non-negative relationship. Table 9 presents the results from the correlation t-tests.

Table 8: Results from independent samples t-tests examining equality of group means

Predictor	**Test-Statistic**	**P-Value**
ACT Math Score	$t(68.05) = -4.93$	$p < .001$
ACT Reading Score	$t(238) = -0.52$	.60
High School GPA	$t(238) = -2.65$	$p < .01$
Pretest	$t(238) = -4.18$	$p < .001$
Class Size	$t(238) = 2.27$	$p < .05$

Table 9: Results from Pearson's Correlation Analysis examining relationship between quantitative predictors and final exam score

Predictor	**Test-Statistic**	**P-Value**	**95% Confidence Interval Lower**	**95% Confidence Interval Upper**	**Correlation Coefficient (r)**
ACT Math Score	$t(238) = -1.50$	.13	-0.22	.03	-0.10
ACT Reading Score	$t(238) = -1.78$	.08	-0.23	.01	-0.11
High School GPA	$t(238) = .77$	.44	-0.08	.18	0.05
Pretest	$t(238) = -1.00$	.32	-0.19	.06	-0.06
Class Size	$t(238) = -1.31$	.19	-0.21	.04	-0.08

A paired t-test was performed on the pretest and final exam. Both exams were the same test, so an analysis can be conducted to see if there was an improvement in the score. The mean difference in pretest and final exam scores are 19.68(27.05). There was statistical significance that the mean difference in scores is not zero ($t(239) = 11.27$, $p < .001$). Thus, there was an improvement in students score on the final exam compared to the pretest score. The results from the paired t-test are presented in Table 10.

Table 10: Results from pairwise t-test with pretest and final exam

Predictor	**Mean Difference(SD)**	**Test-Statistic**	**P-Value**	**95% Confidence Interval for Mean Difference**
Pretest and Final Exam Scores	19.68(27.05)	$t(239) = 11.27$	$p < .001$	(16.24, 23.12)

Data Analysis

This section reviews the hypotheses and presents the findings of each research question.

Multicollinearity is an assumption for both logistic regression and multiple regression that needs to be checked to ensure that there is no high correlation between predictors. The variance inflation factor (VIF) was checked for each predictor and is presented in table 11. All VIF values are under 10 and do not raise concern for multicollinearity. The correlation between the quantitative predictors is also presented in table 12.

Table 11: VIF of logistic regression model and multiple regression models

Predictor	VIF (Standard Logistic Regression Model)	VIF (Standard Multiple Regression Model)
Gender	1.22	1.16
AA.W	1.22	1.22
H.W	Excluded from model	Excluded from model
A.W	Excluded from model	Excluded from model
AI.W	1.04	Excluded from model
U.W	1.05	1.04
TM.W	1.10	1.07

Pell Grant	1.15	1.11
First Generation	1.08	1.07
ACT Math	1.24	1.12
ACT Reading	1.37	1.32
High School GPA	1.25	1.26
Pretest	1.14	1.19
Class Size	3.22	2.01
Number of Class Meetings	3.06	1.94
Afternoon.Morning	1.69	1.56
Afternoon.Evening	1.19	1.25

Note: Race dummy variable abbreviations: H.W = comparison of Hispanic to White, A.W = comparison of Asian to White, AA.W = comparison of African American to White, AI.W = comparison of American Indian to White, U.W = comparison of unknown to White, TM.W = comparison of Multiracial to White.

Note: Time of day dummy variable abbreviations: Afternoon.Morning = comparison of afternoon classes to morning classes, Afternoon.Evening = comparison of evening classes to morning classes.

Table 12: Correlation matrix of predictor quantitative variables

	ACT Math Score	**ACT Reading Score**	**High School GPA**	**Pretest**	**Class Size**
ACT Math Score	1	.19	.01	.23	.10
ACT Reading Score	.19	1	.12	.08	.39
High School GPA	.01	.12	1	.08	.11
Pretest	.23	.08	.08	1	.05
Class Size	.10	.39	.11	.05	1

Research Question 1: Are student, instructor, and/or classroom characteristics predictive of success in developmental math courses?

Hypothesis: ACT Math score, math pretest score, ACT Reading scores, and HSGPA will be significant student predictors. Employment status will be a significant instructor predictor. Number of class meetings in a week will be a significant classroom predictor.

A standard logistic regression analyses were performed on success in the developmental mathematics course (pass/fail) as the outcome and the predictors of this study. The student predictors are gender, race, socioeconomic status determined by Pell-Grant eligibility, first generation status, ACT math score, ACT reading score, high school GPA, and pretest score. Due to race being a categorical variable, dummy variables had to be created which each are compared to the reference group which was White in this case. Two of the dummy variables, H.W and A.W, had to be eliminated due to high standard error values which could alter the accuracy of the model. H.W compared Hispanic to White while A.W compared Asian to White. The representations for the other dummy variables for race are as follows: AA.W = comparison of African American to White, AI.W = comparison of American Indian to White, U.W = comparison of unknown to White, and TM.W = comparison of Multiracial to White. The classroom predictors are class size, number of meetings per week, and time of day. Dummy variables had to be created for time of day and are as follows: Afternoon.Morning = comparison of afternoon classes to morning classes and Afternoon.Evening = comparison of evening classes to morning classes. The standard logistic regression model was statistically significant, $\chi^2(16, N = 240) = 67.3$, $p < .001$. The variance in success in the course accounted for is small with McFadden's rho = .28, df = 16. Using .05 as the threshold, the percentage of accurately classified cases was 185 of 240 or 77.08% with sensitivity and specificity values of 1 and .77, respectively.

Table 13 shows the results from the standard logistic regression analysis including classroom predictors. ACT math score is statistically significant in predicting student success in the developmental mathematics course, $z = 4.84$, $p < .001$. High school GPA is also statistical significant in predicting student success, $z = 2.69$, $p < .01$. Another statistical significant student predictor is the pretest score, $z = 2.54$, $p < .05$. Class size is a statistical significant classroom predictor, $z = -2.53$, $p < .05$.

Table 13: Logistic regression analysis of success in the course as a function of student predictors and classroom predictors

Student Predictor	*B*	Wald (z-ratio)	Odds Ratio	P-Value	95% C.I. Lower	95% C.I. Upper
Gender	-0.12	.40	.89	.77	.40	1.96
AA.W	.38	.75	1.47	.45	.55	4.21
AI.W	-1.28	-0.85	.28	.39	9.66e-03	7.86
U.W	-0.09	-0.11	.92	.92	.20	5.19
TM.W	-0.13	-0.12	.87	.91	.13	.18
Pell Grant	.45	1.12	1.57	.26	.71	3.47
First Generation	.14	.36	1.15	.72	.53	2.45
ACT Math	.77	4.84	2.16	< .001	1.61	3.01
ACT Reading	.01	.19	1.01	.85	.91	1.12
High School GPA	.95	2.69	2.58	< .01	1.32	5.27
Pretest	.04	2.54	1.04	< .05	1.01	1.07
Class Size	-0.14	-2.53	.87	< .05	.77	.96
Number of Class Meetings	.30	.68	1.34	.67	.37	5.57
Afternoon.Morning	-0.10	-0.21	.91	.84	.35	2.28
Afternoon.Evening	.77	.64	2.17	.52	.26	4.77
Intercept (Constant)	-12.12	-4.56	5.43e-06	< .001	2.04e-08	7.29e-04

Note: Race dummy variable abbreviations: H.W = comparison of Hispanic to White, A.W = comparison of Asian to White, AA.W = comparison of African American to White, AI.W = comparison of American Indian to White, U.W = comparison of unknown to White, TM.W = comparison of Multiracial to White.

Note: Time of day dummy variable abbreviations: Afternoon.Morning = comparison of afternoon classes to morning classes, Afternoon.Evening = comparison of evening classes to morning classes.

The standard logistic regression analysis including classroom predictors was followed up by a forward selection logistic regression analysis with H.W and A.W still eliminated from the model. After 5 Fisher Scoring iterations, a significant reliable reduced model appears, χ^2 (6, N = 240) = 1102.7, $p < .001$ with 5 predictors: ACT math score, pretest score, high school GPA, class size, and Pell-Grant status. Using .05 as the threshold, the percentage of accurately classified cases was 185 of 240 or 77.08% with sensitivity and specificity values of 1 and .77, respectively.

Table 14 presents the forward selection logistic regression results of the 4 remaining predictors. ACT math score is statistically significant in predicting student success in the developmental mathematics course, $z = 4.49$, $p < .001$. High school GPA is also statistically significant in predicting student success, $z = 2.80$, $p < .01$. Another statistical significant student predictor is the pretest score, $z = 2.68$, $p < .01$. Class size is a statistical significant classroom predictor, $z = -3.47$, $p < .001$. Even though Pell-Grant status was not statistically significant, the predictor was kept in the reduced model after the forward selection.

Table 14: Forward selection logistic regression analysis of student success with student predictors and classroom predictors, Reduced Model

Student Predictor	*B*	Wald (z-ratio)	Odds Ratio	P-Value	95% C.I. Lower	95% C.I. Upper
ACT Math	.75	4.97	2.12	< .001	1.60	2.90
Pretest	.04	2.68	1.04	< .01	1.01	1.06
High School GPA	.91	2.80	2.49	< .01	1.33	4.84
Class Size	-0.11	-3.47	.89	< .001	.98	.99
Pell-Grant	.58	1.51	1.79	.13	.84	3.80

Intercept (Constant)	-12.09	-4.86	5.64e-06	< .001	3.06e-08	5.54e-04

The reduced model produced is a better fit indicated by the Akaike information criterion (AIC) and chi-square model comparison. AIC evaluates the fit of the model and the smaller the AIC means be better the fit the model is. The AIC of the standard logistic regression model is 225.48 while the AIC of the forward selection logistic regression model is 207.88. The forward logistic regression model was used to determine cut off points to create appropriate sensitivity and specificity. A ROC curve (receiver operating characteristics) was created and is shown in figure 6. The area of the curve for the set of predictors was found to be .83. Figure 7 presents the plot of model sensitivity and specificity for various cut off points and the sensitivity and specificity is at .78 and .72 respectively.

Figure 6: ROC Curve, Forward Logistic Regression Model

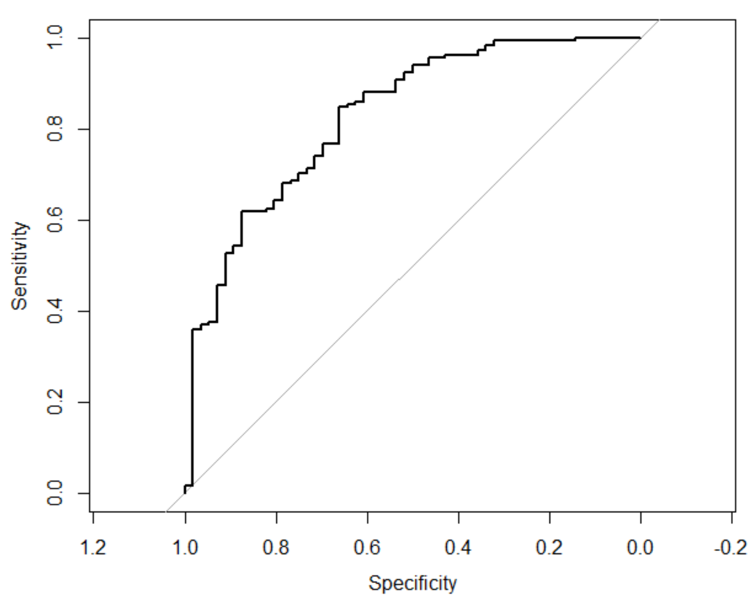
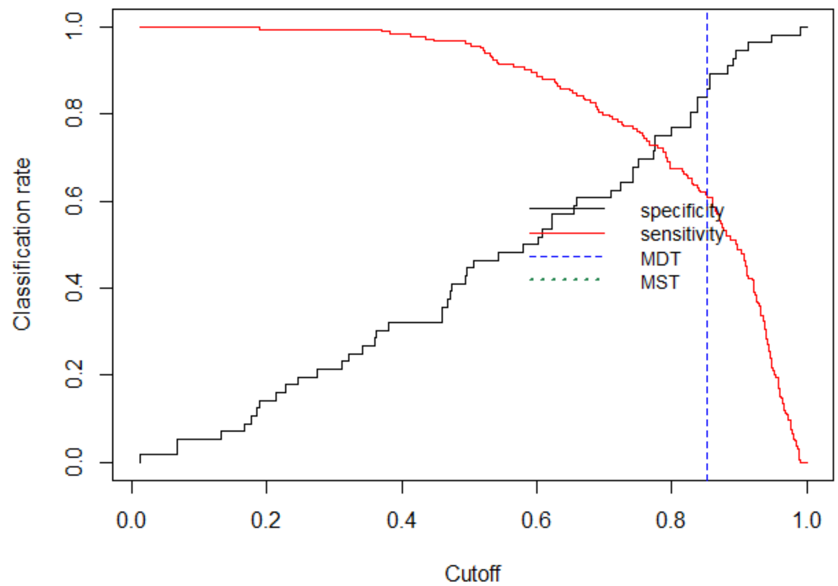


Figure 7: Plot of forward logistic model sensitivity and specificity for various cutoffs



To examine the relationship of the predictors and success in the course further, a backward elimination logistic regression model was conducted. After 5 Fisher scoring iterations, a statistical significant model appeared, $\chi^2(6, N= 240) = 74483.0$, $p < .001$, with five predictors remaining after the eliminations: Pell-Grant status, ACT math score, high school GPA, pretest score, and class size. Those are the same predictors selected by the forward selection. Using .05 as the threshold, the percentage of accurately classified cases was 185 of 240 or 77.08% with sensitivity and specificity values of 1 and .77, respectively.

Table 15 presents the findings of the backward elimination logistic regression analysis. ACT math score is statistically significant in predicting student success in the developmental mathematics course, $z = 4.97$, $p < .001$. High school GPA is also statistical significant in predicting student success, $z = 2.80$, $p < .01$. Another statistical significant student predictor is the pretest score, $z = 2.68$, $p < .01$. Class size is a statistical significant classroom predictor, z = -

3.47, p < .001. Even though Pell-Grant status was not statistically significant, the predictor was also kept in the reduced model after the backward elimination.

Table 15: Backward elimination logistic regression analysis of student success with student predictors and classroom predictors, Reduced Model

Student Predictor	*B*	Wald (z-ratio)	Odds Ratio	P-Value	95% C.I. Lower	95% C.I. Upper
ACT Math	.75	4.97	2.12	< .001	1.60	2.90
Pretest	.04	2.68	1.04	< .01	1.01	1.07
High School GPA	.91	2.80	2.49	< .01	1.34	4.84
Class Size	-0.11	-3.47	.89	< .001	.84	.95
Pell-Grant	.58	1.51	1.79	.13	.84	3.80
Intercept (Constant)	-12.09	-4.86	5.64e-06	< .001	3.06e-08	.55e-03

Research Question 2: Are student, instructor, and/or classroom characteristics predictive of success on the final exam?

Hypothesis: ACT Math score, math pretest score, ACT Reading scores, and HSGPA will be significant student predictors. Employment status will be a significant instructor predictor. Number of class meetings in a week and time of day will be significant classroom predictors.

A standard multiple regression analysis was conducted with only student predictors. Three of the dummy variables for race, H.W, A.W, and AI.W were taken out of the analysis due to high standard error values. H.W compared Hispanic to White, A.W compared Asian to White, and AI.W compared American Indian to White. Linearity, independence, homogeneity of variances, and normality are four assumptions that need to be checked for multiple regression analysis. A scatter plot of the residuals and predicted values can be used to verify linearity and independence when there is no funneling out or a curve pattern. Figure 8 shows the scatter plot of residuals and predicted values which shows no evidence of funneling out or a curve pattern, thus we can assume linearity and independence. Homogeneity of variance can also be verified using the same scatter plot by analyzing the distance on each side of zero to see if the overall distance on each side is the same. Overall, there is no concern that the homogeneity of variance assumption has been violated. A histogram of the residuals and a normal qq-plot can be used to verify the normality assumption and are presented in figures 9 and 10. The histogram gives no indication that normality has been violated. The closer the points are to the line on the qq-plot the better and overall the qq-plot created doesn't give too much concern for normality.

Figure 8: Scatter plot of the residuals and predicted values

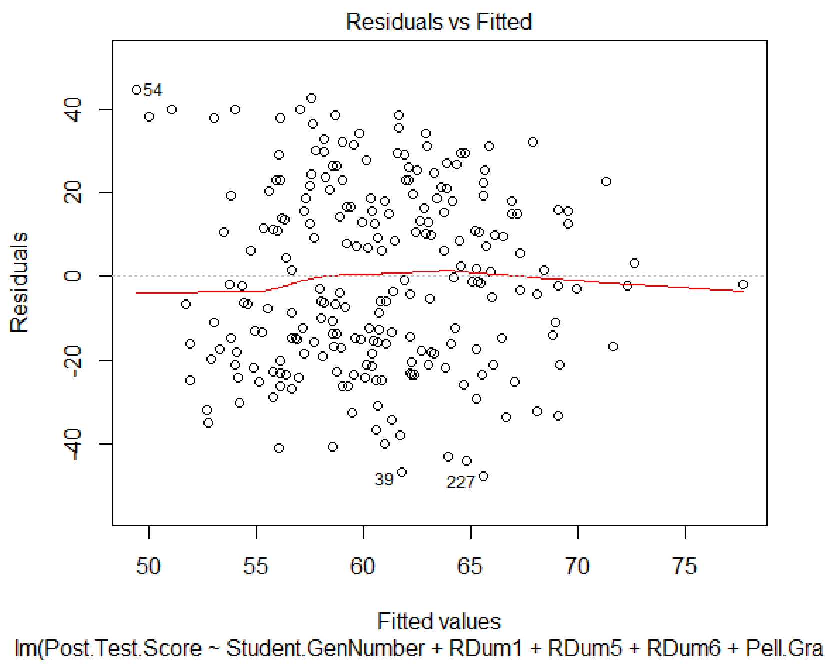


Figure 9: Normal qq-plot

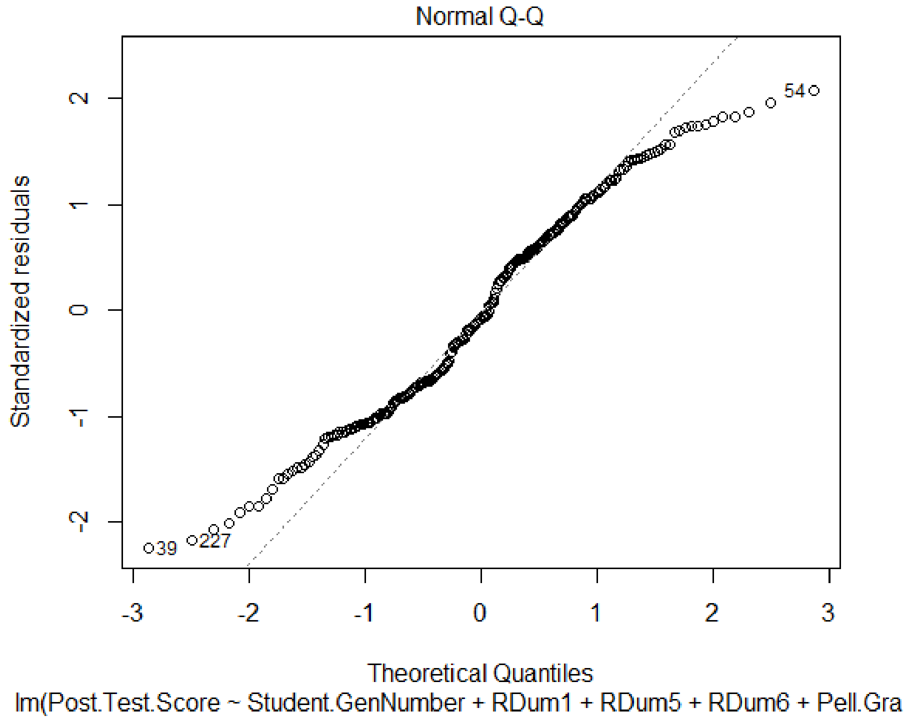
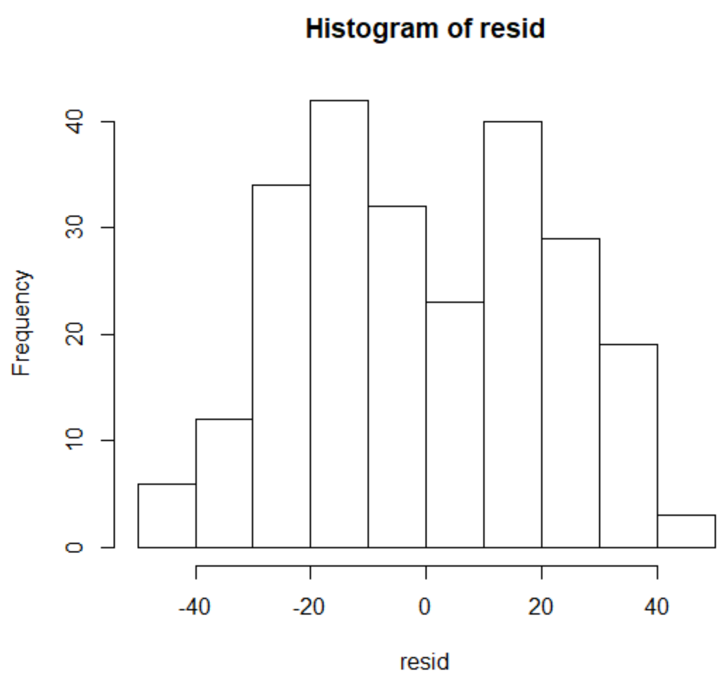


Figure 10: Histogram of the residuals



Results of the multiple regression analysis are presented in table 16 and table 17. A non-significant model was found (F(14, 225) = .76, p = .71) with an adjusted R-square of -0.01. No predictors were statistically significant.

Table 16: Standard Multiple Regression Model Summary

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
Gender	3.18	3.12	1.02	.31
AA.W	.27	4.19	.07	.95
U.W	1.59	6.74	.24	.81
TM.W	7.47	7.45	1.00	.32
Pell Grant	-2.48	3.23	-0.77	.44
First Generation	.59	3.14	.19	.85
ACT Math	-1.17	1.04	-1.12	.26
ACT Reading	-0.47	.41	-1.12	.26
High School GPA	3.17	2.67	1.19	.24
Pretest	-0.12	.11	-1.11	.27
Class Size	-0.11	.36	-0.30	.76
Number of Class Meetings	1.32	4.49	.29	.77
Afternoon.Morning	3.96	3.62	1.10	.27
Afternoon.Evening	3.74	8.06	.46	.64
Intercept (Constant)	81.90	19.01	4.31	2.45e-05

Note: Race dummy variable abbreviations: H.W = comparison of Hispanic to White, A.W = comparison of Asian to White, AA.W = comparison of African American to White, AI.W = comparison of American Indian to White, U.W = comparison of unknown to White, TM.W = comparison of Multiracial to White.

Note: Time of day dummy variable abbreviations: Afternoon.Morning = comparison of afternoon classes to morning classes, Afternoon.Evening = comparison of evening classes to morning classes.

Table 17: ANOVA table for standard multiple regression model

Model	Sum of Squares	Degrees of Freedom	Mean Squares	F	P-Value	Adjusted R-Squared
Regression	5300	14	378.57	.76	.71	-0.01
Error	112051	225	498.00			
Total	117351	239				

The standard multiple regression analysis was followed up by a forward selection multiple regression analysis. A non-significant model was found (F(1, 238) = 3.18, p = .08) with an adjusted R-square of .01. ACT reading score was the only predictor kept in the model despite it not being statistically significant. Results of the forward selection multiple regression analysis is presented in tables 18 and 19.

Table 18: Forward Selection Multiple Regression Model Summary

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
ACT Reading	-0.64	.36	-1.78	.08
Intercept	71.33	6.13	11.64	< .001

Table 19: ANOVA table for forward selection multiple regression model

Model	Sum of Squares	Degrees of Freedom	Mean Squares	F	P-Value	Adjusted R-Squared
Regression	1548	1	1548	3.18	.08	0.01
Error	115802	238	486.56			
Total	117350	239				

To further examine the predictors, a backward elimination multiple regression analysis was conducted. Results of the backward elimination multiple regression analysis is presented in tables 20 and 21. A non-significant model emerged (F(2, 237) = 5.19) with an adjusted R-square of .01. ACT math and Afternoon.Morning (compares afternoon classes to morning classes) was the predictors kept in the model even though they were not statistically significant.

Table 20: Backward elimination multiple regression model summary

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
ACT Math	-1.42	.97	-1.47	.14
Afternoon.Morning	4.87	2.85	1.71	.09
Intercept	80.43	15.12	5.32	< .001

Note: Time of day dummy variable abbreviation: Afternoon.Morning = comparison of afternoon classes to morning classes.

Table 21: ANOVA table for backward elimination multiple regression model

Model	Sum of	Degrees of	Mean	F	P-Value	Adjusted

	Squares	Freedom	Squares			R-Squared
Regression	2515	2	2515	5.19	.08	.01
Error	114835	237	484.54			
Total	117350	238				

Research Question 3: Is the student predictor Race X SES a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

Hypothesis: Race X SES will be statistically significant when controlling for high school GPA.

Regression techniques were used to test the significance of the interaction between race and socioeconomic status determined by Pell-Grant status. First a model without controlling for high school GPA (without a covariate) was conducted and the results are presented in table 22. None of the predictors came out statistically significant. The model created was non-significant in predicting student success in the developmental mathematics course. An ANOVA table is shown in table 23.

Table 22: Regression model summary without covariate

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
Race Asian American (AS)	1.00	.60	1.65	.10
Race African American (B)	-0.17	.46	-0.36	.72
Race Hispanic (H)	2.30e-15	.60	0	1.00
Race Multiracial (T)	-0.25	.48	-0.52	.60
Race Unknown (U)	-0.20	.47	-0.43	.67
Race White (W)	-0.70	.43	-0.63	.53
Pell Grant	-1.00	.60	-1.65	.10
RaceAS:Pell.Grant	N/A	N/A	N/A	N/A
RaceB:Pell.Grant	.89	.63	1.40	.16
RaceH:Pell.Grant	1.00	.80	1.25	.21
RaceT: Pell.Grant	1.25	.66	1.88	.06

RaceU:Pell.Grant	.91	.65	1.40	.16
RaceW:Pell.Grant	1.06	.61	1.73	.08
Intercept	1.00	.43	2.34	< .05

Table 23: ANOVA table for regression model without covariate

Model	Sum of Squares	Degrees of Freedom	Mean Squares	F	P-Value	Adjusted R-Squared
Regression	1.43	12	.12	.65	.80	-0.02
Error	41.50	227	.18			
Total	42.93	239				

After conducting an analysis without a covariate, high school GPA was added to the model as a covariate and the results are presented in table 24. The interaction between Multiracial and SES when controlling for high school GPA is statistically significant ($B = 1.39$, $t(226) = 2.12$, $p < .05$) and high school GPA is also statistically significant ($B = .14$, $t(226) = 2.98$, $p < .01$). The model created was non-significant in predicting student success in the developmental mathematics course. An ANOVA table is shown in table 25.

Table 24: Regression model summary with covariate

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
Race Asian American (AS)	1.02	.59	1.72	.09
Race African American (B)	-0.22	.45	-0.49	.63
Race Hispanic (H)	-0.03	.59	-0.06	.95
Race Multiracial (T)	-0.37	.47	-0.79	.43
Race Unknown (U)	-0.34	.46	-0.74	.46
Race White (W)	-0.41	.43	-0.96	.34
Pell Grant	-1.11	.60	-1.86	.06
High School GPA	.14	.05	2.98	< .01
RaceAS:Pell.Grant	N/A	N/A	N/A	N/A
RaceB: Pell.Grant	1.00	.62	1.60	.11
RaceH: Pell.Grant	1.12	.79	1.42	.16

RaceT: Pell.Grant	1.39	.66	2.12	< .05
RaceU: Pell.Grant	1.05	.65	1.63	.10
RaceW: Pell.Grant	1.18	.60	1.96	.05
Intercept	.71	.43	1.64	.10

Table 25: ANOVA table for regression model with covariate

Model	Sum of Squares	Degrees of Freedom	Mean Squares	F	P-Value	Adjusted R-Squared
Regression	3.00	13	.23	1.31	.21	.02
Error	39.93	226	.18			
Total	42.93	239				

Research Question 4: Is the student predictor Race X Gender a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

Hypothesis: Race X Gender will be statistically significant when controlling for high school GPA.

Regression techniques were used to test the significance of the interaction between race and gender. First a model without controlling for high school GPA was conducted and the results are presented in table 26. None of the predictors came out statistically significant. The model created was non-significant in predicting student success in the developmental mathematics course. An ANOVA table is shown in table 27.

Table 26: Regression model summary without covariate

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
Race Asian American (AS)	.50	.53	.95	.34
Race African American (B)	.20	.32	.60	.54
Race Hispanic (H)	.50	.39	1.28	.20
Race Multiracial (T)	.48	.38	1.27	.20

Race Unknown (U)	.20	.35	.56	.58
Race White (W)	.25	.31	.82	.41
Student GenderM	-0.02	.07	-0.28	.78
RaceAS:GenderM	N/A	N/A	N/A	N/A
RaceB: GenderM	.07	.15	.45	.66
RaceH: GenderM	N/A	N/A	N/A	N/A
RaceT: GenderM	-0.15	.29	-0.52	.60
RaceU: GenderM	.10	.26	.40	.69
RaceW: GenderM	N/A	N/A	N/A	N/A
Intercept	.52	.31	1.67	.10

Table 27: ANOVA table for regression model without covariate

Model	Sum of Squares	Degrees of Freedom	Mean Squares	F	P-Value	Adjusted R-Squared
Regression	.70	10	.07	.38	.95	-0.03
Error	41.50	229	.18			
Total	42.93	239				

After conducting an analysis without a covariate, high school GPA was added to the model as a covariate and the results are presented in table 28. High school GPA is came out to be statistically significant ($B = .14$, $t(228) = 2.77$, $p < .01$). The model created was non-significant in predicting student success in the developmental mathematics course. An ANOVA table is shown in table 29.

Table 28: Regression model summary with covariate

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
Race Asian American (AS)	.47	.52	.90	.37
Race African American (B)	.22	.32	.67	.50
Race Hispanic (H)	.52	.39	1.36	.18
Race Multiracial (T)	.43	.37	1.15	.25
Race Unknown	.19	.35	.537	.59

(U)				
Race White (W)	.20	.30	.66	.51
Student GenderM	.02	.07	.31	.75
High School GPA	.13	.05	2.77	< .01
RaceAS:GenderM	N/A	N/A	N/A	N/A
RaceB: GenderM	.07	.15	.45	.65
RaceH: GenderM	N/A	N/A	N/A	N/A
RaceT: GenderM	-0.12	.28	-0.41	.68
RaceU:GenderM	.02	.26	.93	.93
RaceW:GenderM	N/A	N/A	N/A	N/A
Intercept	.14	.34	.43	.67

Table 29: ANOVA table for regression model with covariate

Model	Sum of Squares	Degrees of Freedom	Mean Squares	F	P-Value	Adjusted R-Squared
Regression	2.07	11	.19	1.05	.40	.002
Error	40.86	228	.18			
Total	42.93	239				

Research Question 5: Is the student predictor SES X First Generation Status a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

Hypothesis: SES X First Generation Status will be statistically significant when controlling for high school GPA.

Regression techniques were used to test the significance of the interaction between SES determined by Pell-Grant status and first generation status. First a model without controlling for high school GPA was conducted and the results are presented in table 30. None of the predictors came out statistically significant. The model created was non-significant in predicting student success in the developmental mathematics course. An ANOVA table is shown in table 31.

Table 30: Regression model summary without covariate

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
Pell Grant	-0.06	.09	-0.64	.52
First Generation	-0.05	.10	-0.53	.60
Pell.Grant:First.Gen	.13	.12	1.09	.28
Intercept	.78	.07	10.98	< .001

Table 31: ANOVA table for regression model without covariate

Model	Sum of Squares	Degrees of Freedom	Mean Squares	F	P-Value	Adjusted R-Squared
Regression	.298	3	.07	.55	.65	-0.01
Error	42.64	236	.18			
Total	42.93	239				

After conducting an analysis without a covariate, high school GPA was added to the model as a covariate and the results are presented in table 32. High school GPA is came out to be statistically significant ($B = .12$, $t(235) = 2.72$, $p < .01$). The model created was non-significant in predicting student success in the developmental mathematics course. An ANOVA table is shown in table 33.

Table 32: Regression model summary with covariate

Predictor	Estimate (B)	Standard Error	T-Value	P-Value
Pell Grant	-0.04	.09	-0.46	.64
First Generation	-0.05	.09	-0.57	.57
High School GPA	.12	.05	2.72	< .01
Pell.Grant:First.Gen	.13	.05	1.13	.26
Intercept	.42	.15	2.81	< .01

Table 33: ANOVA table for regression model with covariate

Model	Sum of Squares	Degrees of Freedom	Mean Squares	F	P-Value	Adjusted R-Squared
Regression	1.60	4	.40	2.28	.06	.02
Error	41.33	235	.18			
Total	42.93	239				

Summary

The results of the data analyses were presented in this chapter. The purpose of this study is to examine potential predictors of success with the objective of exposing areas of potential improvement to developmental mathematics courses. The descriptive statistics were reviewed along with the results from the subtests for each predictor and the tests for the assumptions. Logistic regression techniques were implemented for the analysis of research question 1. After a forward selection logistic regression analysis, 5 of the predictors remained which were ACT math score, pretest, high school GPA, class size, and Pell-Grant status. Out of the remaining predictors, Pell-Grant status was not statistically significant even though it remained in the model. The reduced model produced after the forward selection was a better model compared to the original model with all the predictors indicated by the AIC and chi-square model comparison. Multiple regression techniques were used to analyze research question 2 and none of the predictors came out significant. Similar techniques were used to analyze research questions 3, 4, and 5. Regression and ANOVA techniques were used in the analyses of this study. For all 3 research questions, none of the predictors or interactions was statistically significant for the first model without high school GPA as the covariate. Research question 3 analyzed the interaction between race and SES (determined by Pell-Grant status) and the interaction between Multiracial and Pell-Grant status was statistically significant along with high school GPA after the addition of high school GPA as a covariate. After adding high school GPA as a covariate for research question 4 and 5, high school GPA was the only predictor found to be statistically significant. The discussion and conclusion of these findings will be presented in the next chapter of this study.

CHAPTER V: SUMMARY

This chapter will review the overall study and discuss the findings from the previous chapter. Recommendation for future research will also be presented. The purpose of this study is to expose any areas of possible improvement to developmental mathematics courses by analyzing potential predictors of success. Based on the predictors of this study, are there areas of improvement that need to be made to the developmental mathematics course so that student success and retention increases? The research questions of this study sought out to answer that question. The research questions are as follows:

- Research Question 1: Are student, instructor, and/or classroom characteristics predictive of success in developmental math courses?
- Research Question 2: Are student, instructor, and/or classroom characteristics predictive of final exam score?
- Research Question 3: Is the student predictor Race X SES a significant predictor of success in a developmental mathematics course when controlling for high school GPA?
- Research Question 4: Is the student predictor Race X Gender a significant predictor of success in a developmental mathematics course when controlling for high school GPA?
- Research Question 5: Is the student predictor SES X First Generation Status a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

The findings of this study will also connect to existing literature and will contribute to existing literature. Instructor characteristics were not included in the analysis on the research questions due to lack of variation in the categories. Student age was also excluded due to lack of variation. The predictors that were examined include: student gender, ACT math score, ACT reading score, race, socioeconomic status, first generation status, high school GPA, pretest score, class size, time of day, and number of meetings per week.

Purpose and Significance of Study

Obtaining a college education and a degree is considered to be vital in order to be successful in many cases (Hout, 2012). There is concern with the college readiness of students, particularly in mathematics. As institutions implement open enrollment to everyone, regardless of backgrounds, there is stress on helping students who lack basic skills so that they can be successful in college (Zachry & Schneider, 2012). Institutions want students to be successful and for student retention rates to improve. This study sought out to expose areas of improvement to developmental mathematics courses by examining potential predictors of success. This study was inspired by on a previous study conducted by Linda Hunt in 2011 at Marshall University Community and Technical College. Some variables she suggested for future studies was included in this study including high school GPA, financial need, and reading ability measured by ACT or SAT as potential predictors of success in developmental mathematics. The sample of this study consisted of students previously enrolled in a developmental mathematics course (Math 0101: Basic Algebra with Geometry Application) at Shawnee State University. The statement of the problem of this study asks this: based on the examined predictors of this study, are there ways to makes improvements to the developmental math course that need to be made so that student success and student retention increases? Any information gathered regarding predictors of success in remedial mathematics can help administrators plan on how to improve remedial interventions and thus improve student retention rates and college success (Martinez, 2017).

Importance of Developmental Mathematics and Concern of Risks

Education focused on remediating students who lacked basic skills began as early as the 20th century. As the years went by, developmental education evolved into something more than tutoring alone and any person can take advantage of it (Abraham, 2014). Big events, such as the GI Bill and The Civil Rights Movement in the 1960s, helped every person no matter the background gain a postsecondary education ("The GI Bill," n.d.; "Evolution of Developmental Education," n.d.). The theoretical framework of developmental education was defined as "a comprehensive process which focuses on the intellectual, social, and affective growth and development of all learners at all levels" (Davis, 2014). Developmental mathematics is included in developmental education.

The goal of developmental mathematics is to strengthen students' mathematical understanding and skills so that they will be prepared take college level mathematics so that they can obtain a degree. Previous studies conducted by the researchers who support developmental mathematics shows that developmental mathematics is a good predictor of success in college level mathematics and improved student performance other courses even compared to other students who did not take developmental mathematics (Wolf, 2012; Johnson and Kuennen, 2004). These researchers support developmental mathematics and recommend students to then those courses the first semester of college. However, there exist researchers who oppose developmental mathematics for reasons including costing students more time and money to take courses that do not contribute to their degree (Brasiel, 2017). Which raises the concern that developmental mathematics could be a barrier to students completing their college education and getting a degree (Bonham & Boylan, 2011; Quarles & Davis, 2017)? The cost of remediation is very expensive and when students drop from college, this can result in students accumulating debt they cannot pay off (Bettinger et al., 2013; Bailey, 2009). Knowing the goal of developmental mathematics and the potiental risks that can be associated with it, this study was designed to examine predictors of student success in order to identify areas of possible improvement so that students can be successful in their college career.

Social Integration in Tinto's Theory of Student Retention

Tinto's Theory of Student Retention is the theoretical framework that was selected for this study. Tinto says there are two ways that students can integrate into the college community, social integration and academic integration. One limitation of this study is that it does little to address the social integration component of Tinto's theory, but social integration was addressed in the literature review. Social integration takes place through social connections, such as with other college students and faculty (Tinto, 1975). Students having those relationships and connections are viewed as important and valuable to the college experience (Tinto, 1975). With social integration being considered crucial, a lack of connection could contribute to a student's decision to drop out from college (Tinto, 1975). Social integration could be somewhat different for those students who take developmental mathematics since their experience will be a little different compared to students who did not have to take developmental mathematics (Umoh, 1994).

Alharthi argues that the failure for a first-year student to make friends can lead to that student dropping out of their studies based on the qualitative study conducted to analyze the My Uni-Buddy program at a university to see if students benefited from the program (2020). Students' communication with classmates and faculty has a great impact on emotional functioning and on student success (Aydin, 2017). Aydin found that classroom communication was statistically significant in predicting student success and is something that can alter student success (2017). However, Ishitani did not find statistical significance in social integration for the persistence of first-year students (2016). In Tinto's Theory of Student Retention, it is possible for students to integrate only socially or academically and still be successful (1975). This study focuses on the academic integration aspect of Tinto's theory.

Research Design and Methodology

The variables of this study were characteristics of the students, instructors and classrooms. Student characteristics include gender, age, race, ACT Math score, ACT Reading score, math pretest score, 1st generation status, SES, and high school GPA. Instructor characteristics include gender, degree, and employment status. Classroom characteristics include class size, number of times a class meets per week, and time of day the class meets. The dependent variables in this study will be final exam score and overall grade in the developmental mathematics course.

Prior to data collection, the researcher received IRB approval to proceed with this study. The research design of this study is ex-post facto where the data existed prior to the study and needed to be collected according to the requirements of the study. Data came from student records, department records, class schedules, and the composite pretest scores were kept by the Director of Developmental Mathematics at Shawnee State University. The sample collected for this study consisted of 348 students who were previously enrolled in a developmental mathematics course at Shawnee State University. The semester enrollment dates of students ranged from spring 2017 to fall 2019, also including summer semesters, giving a total of 8 semesters (Spring 2017, Summer 2017, Fall 2017, Summer 2018, Fall 2018, Spring 2019, Summer 2019, and Fall 2019).

The course is Math 0101: Basic Algebra with Geometry Application which provides a foundation of math skills for student who maybe weak in their mathematics skills. The sample size of this study was appropriate according to the specifications given by Andy Field et al. (2012) and a power analysis conducted using G*Power. Field states that the two most common rules are 10 cases per predictor and 15 cases per predictor (Field et al., 2012, p. 273). With this study there are 15 predictors, so the sample size according to the 10 cases per predictor rule should be at least 150. For the 15 cases per predictor rule, the sample size for this study should be 225. The priori power analysis conducted for multiple regression using G*Power and a standard alpha level of .05, power of .80, and a medium effect size indicated by G*Power to be .15 indicated that an adequate sample size should be at least 139.

Each research question of this study required a different statistical approach due to the characteristics of the variables being examined. Before the research questions were addressed, a series of subtests was conducted to examine the predictors individually. Certain assumptions also needed to be checked before the analyses which included linearity, independence, and no multicollinearity. For research question 1, the dependent variable being examined was student success in the course (pass/fail), so logistic regression had to be used since success is a categorical variable. The forward selection logistic regression analysis was conducted which selects certain predictors with the goal of creating a model that best predicts the outcome (Field et al., 2012, p. 264). For research question 2, the dependent variable was final exam score so multiple regression was used to create this model. A forward selection multiple regression analysis was also conducted which is similar to the forward selections logistic regression in how certain predictors are selected to make the best fit model. For the last three research questions, different interactions between variables were tested with similar statistical techniques as the first two research questions. Information found in the literature review inspired the creation of the last three questions.

Discussion of Findings

The data was examined and missing data values was dealt case wise. Cases without an ACT math score, ACT reading score, and pretest score were eliminated. Since high school GPA was measured numerically, any case that obtained a GED and did not have a high school GPA was eliminated. The sample size after the missing cases were dealt with was 240. The description of the participants was given. Due to variability issues, the instructor characteristics and student age was kept out of the analyses. Subtests of the individual predictors were conducted.

Qualitative Predictors: A chi-square test was used when both the outcome and predictors are categorical variables. An independent sample t-test (independent variable has two categories) and ANOVA (independent variable has more than two categories) is required when the independent variable is categorical and the dependent variable is quantitative.

Quantitative Predictors: An independent t-test was conducted to see if there is a mean difference in the quantitative predictors across pass or fail in the course. In addition, a Pearson Correlation Analysis conducted to examine the relationship between the quantitative predictors and final exam score.

Additionally, a paired t-test was conducted on pretest and final exam score to see if students' scores improved from the beginning of the course to the end of the course. Statistically significance was found in the mean difference in pretest and final exam scores. This would mean that there was an improvement in students' scores when comparing the final exam score to the pretest students took at the beginning of class.

The results of each research question will be discussed. Assumptions of the statistically techniques were tested before proceeding with the analyses.

Research Question 1: Are student, instructor, and/or classroom characteristics predictive of success in developmental math courses?

Logistic regression techniques were used for the analysis of this question. After running a standard logistic regression analysis on all the predictors, a forward selection logistic regression analysis was conducted. ACT math score, pretest, high school GPA, class size, and Pell-Grant status were the 5 predictors that remained in the model. The reduced model produced by forward selection logistic regression analysis was a better model compared to the standard model with all the predictors indicated by the AIC and chi-square model comparison. A backward elimination logistic regression analysis selects predictors to create the best model similarly to the forward selection, but it will start with all the predictors then eliminate them to create the best fit model. A backward elimination logistic regression analysis was conducted to further examine the predictors. ACT math, pretest, high school GPA, class size, and Pell-Grant status was left in the model similarly to the forward selection model. When interpreting the odds ratio in terms of the change in the odds, a value greater than 1 indicates that as the predictor increases, the odds of the outcome occurring increases (Field et al., 2012, p. 336). Conversely, a value that is less than one indicates as the predictor increases then the odds of the outcome occurring decreases (Field et al., 2012, p. 336).

ACT math score was found to be statistically significant in predicting student success in a developmental mathematics course in this study. The odds ratio of ACT math score tells us that as the score increases by one unit, the change in the odds of success is 2.12. In a previous study, ACT math score was found to be a significant predictor student success in both elementary algebra and intermediate algebra which are developmental mathematics courses (Hunt, 2011). Even though ACT math was not significant for elementary algebra in Stephen's study, the ACT math score was significant for intermediate algebra, a developmental math course, and a non-developmental math course (2005).

Pretest was found to be significant in predicting success in developmental math in this study. The odds ratio of pretest score tells us that as the score increases by one unit, the change in the odds of success is 1.04. In Hunt's study, pretest was the strongest predictor of student success in developmental mathematics (2011). In an ANCOVA analysis, pretest was found to be significant when using a nonrandomized control group pretest-posttest design to compare developmental mathematics student performance (Spradlin, 2010). High school GPA was found to be statistically significant in this study. The odds ratio high school GPA tells us that as the GPA increases by one unit, the change in the odds of success is 2.49. Stephen found high school GPA to be a good predictor of student success in both developmental math courses in his study (2005).

Even though SES (determined by Pell-Grant status) was left in the reduced model it was not statistically significant. The odds ratio of Pell-Grant tells us that as Pell-Grant changes from not having a Pell-Grant to having a Pell-Grant, the change in the odds of success is 1.79. It was found in a previous study that full-time students with financial aid have higher odds of persisting through all the levels of developmental mathematics compared to students who were part-time and did not obtain financial aid (Fong, 2015). Source of tuition, categorized as loans, grants, scholarships, and other, was included in a developmental mathematics predictor model and all sources were non-significant (Martinez, 2017). Pell-Grant eligibility was included in Ran's study, which compared part-time faculty and full-time faculty's impact on student success in courses including developmental math, and found Pell-Grant eligibility to be a significant predictor of student success (2019). Class size was found to be a significant predictor of student success in developmental mathematics in this study. The odds ratio of class size tells us that as the class size increases by one unit, the change in the odds of success is .89. Fong's study found that for each additional student enrolled in a developmental mathematics course that the odds of students being successful and passing decreased and smaller class sizes were associated with greater chance of success (2015).

Research Question 2: Are student, instructor, and/or classroom characteristics predictive of final exam score?

Multiple regression was used to examine the predictors to see any were significant predictors of final exam score. In standard multiple regression analysis, no predictors were found to be statistically significant. Both forward selection multiple regression analysis and backward elimination multiple regression analysis work similarly to the forward selection logistic regression and backward elimination logistic regression analysis described previously. A forward selection multiple regression analysis and backward elimination multiple regression analysis was also conducted which neither model was significant nor the predictors left in the models. The ACT reading score was the only predictor left in the forward selection multiple regression model. The ACT math score and the comparison of afternoon classes to morning classes (Afternoon.Morning) was the predictors left in the backward elimination multiple regression model.

Both the logistic regression models and the multiple regression models are completely different. That brings into question whether the success in the course is related to final exam score. Based on the analyses in this study, there is no observed relation between the final exam score and success in the course. The predictors that were significant in the logistic regression model predicting success were not significant in the multiple regression predicting final exam score. The relationship between the final exam score and success in the course could be further examined in another study.

Results from previous studies inspired the creation of research questions 3, 4, and 5. In Fong's study, it was found that females have better odds of succeeding at every stage of developmental mathematics compared to male students (2015). Fong (2015) also found the African American and Latino students were less likely to advance through the levels of developmental mathematics courses or passing at each level. Fong also said that students who received financial aid and who were full time were more likely to persevere through different levels of developmental mathematics (2015). Engle claims that first generation college students are more likely to be female, African American or Hispanic, and come from low-income households which are connected with low college attendance rates and completion of a degree (2007). Guerrero et al. (2020) found that first generation students were 5% to 7% less likely to succeed at the non-credit mathematics courses analyzed in their study.

Research Question 3: Is the student predictor Race X SES a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

Regression techniques were used to test the significance of the interaction between race and socioeconomic status determined by Pell-Grant status using high school GPA as a covariate. An analysis without a covariate was conducted which found no predictor significant and the model and non-significant as well. After adding the covariate, high school GPA and the interaction between Multiracial and SES was statistically significant, but the model was non-significant.

Research Question 4: Is the student predictor Race X Gender a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

Regression techniques were used to test the significance of the interaction between race and gender. An analysis without a covariate was conducted which found no predictor significant and the model and non-significant as well. After adding the covariate, high school GPA was statistically significant, but the model was non-significant.

Research Question 5: Is the student predictor SES X First Generation Status a significant predictor of success in a developmental mathematics course when controlling for high school GPA?

Regression techniques were used to test the significance of the interaction between SES determined by Pell-Grant status and first generation status. An analysis without a covariate was conducted which found no predictor significant and the model and non-significant as well. After adding the covariate, high school GPA was statistically significant, but the model was non-significant.

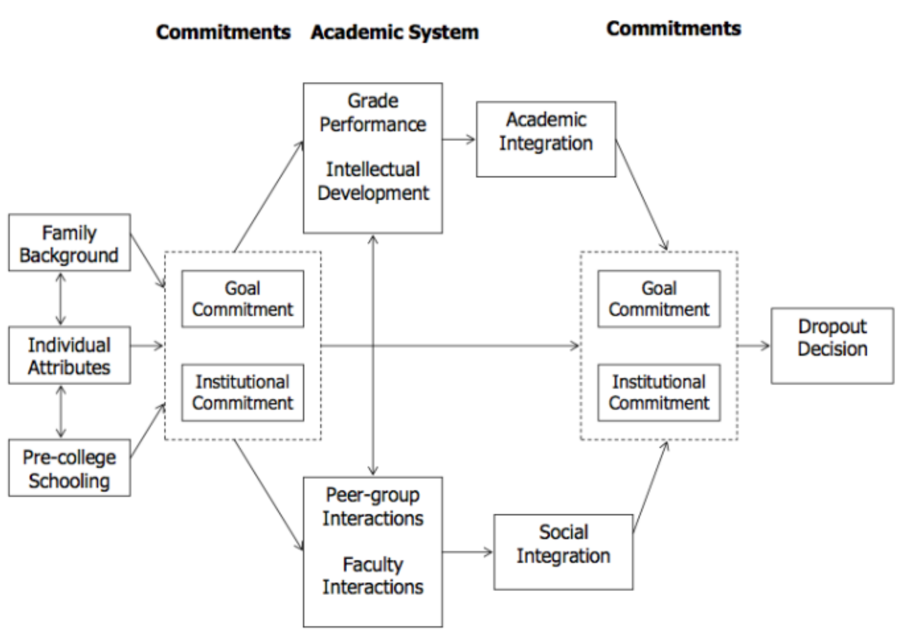
Theoretical Framework and the Results

How do the results of this study tie into the theoretical framework? Tinto's Theory of Student Retention is the theoretical framework of this study which was developed with the goal of explaining why students dropout from universities and colleges. The theory was created based on Durkheim's Theory of Suicide which claims that people are more likely to commit suicide if they are not integrated into society (Tinto, 1975). College or universities are viewed as its own social system with values and social customs which a student dropping out can be compared to an individual committing suicide in a community (Tinto, 1975). Tinto names several characteristics that students come into college with including individual attributes (gender, race, ability), family background (social status, value climates), and precollege experiences (GPA, academic and social attainments) (1975). Tinto suggests that these backgrounds and attributes can affect how students do in college and impacts the development of educational expectations and commitments that they bring with them to college (1975). The expectations and commitments students set for themselves and the college commitments are significant factors in students' experience in college. The goal commitment is referring to the willpower a student has to complete college and obtain a degree and institutional commitment refers to the willingness to obligate to a particular college a student is attending such as financial and time commitments (1975). Students who are required to take developmental courses enter into college with expectations and commitments similarly to students who are not required to take developmental courses. Developmental courses are non-credit courses, so the fact that these students who have to take developmental courses are willing to take a non-credit course adds another layer to their commitment to earning a degree.

Tinto next describes the academic integration and social integration of his theory. This study does not address the social integration of the theory, but can be included in a future study. Academic integration refers to grade performance and intellectual development which this study focuses on. Final Exam score and Overall Grade in the developmental mathematics course is the measurement of academic integration. After the integration into the college community, the theory leads back to the goal and institutional commitments which can lead to a student decision to drop out. The success in one course can increase the chances of success in a student's college career.

The more that is known about the reasons why students succeed or don't succeed makes it possible to make changes to courses in order to increase the chances of students being successful. This study selected a group of predictors and analyzed them to see if any are significant predictors of success and final exam score. ACT math score, pretest score, high school GPA, and class size were significant predictors of success in the course in the reduced model and SES was left in the model despite it not being significant. The characteristics that were under the pre-college schooling category of Tinto's theory are ACT math score, high school GPA, and pretest score. SES is in the family background category of Tinto's theory. No characteristics were in the individual attributes category. There were no significant predictors of final exam score in this study and no significant model was created when testing the interactions for research questions 3, 4, and 5. Recall the Conceptual Schema for Dropout from College in figure 11 from Tinto's Theory of Student Retention from chapter 1 of this study (1975).

Figure 11: Recall A Conceptual Schema for Dropout from College, (Tinto 1975)



<u>Recommendations</u>

Over 40% of students entering their first year of college are not prepared for college level course work and require remediation (Martinez, 2017). Due to this issue, many institutions sought out the reasons why remedial mathematics students fail and others search for factors that could help these students succeed (Martinez, 2017). This study examined a group of factors that could be likely to predict success of students in developmental mathematics with the goal of gaining a better understanding so that improvements can be made to help students succeed in developmental mathematics. If students can succeed in developmental mathematics, then they will have better chances of being successful in college and obtaining a degree.

The reduced model after the forward selection logistic regression analysis was a better fit compared to the original model that included all the predictors. ACT math score, pretest score, high school GPA, and class size were significant predictors of success in the course and SES was left in the model despite SES not being significant. A paired t-test was performed on the pretest and final exam to see if there was an improvement in students' scores. There was evidence in the analysis to conclude that there was an improvement in the final exam score compared to the pretest score. Instructors of this course could continue to implement a pretest and posttest or final exam in the future.

There are some suggestions for future studies. Due to the major difference between the logistic regression models predicting success and the multiple regression models predicting final exam score, it might be good to further analyze the relationship between final exam score and success in the course. The developmental mathematics course that was analyzed in this study was an elementary mathematics course, Math 0101: Basic Algebra with Geometry & Application. This study could be replicated to examine an intermediate algebra course which is also a developmental mathematics course. Hunt (2011) examined an intermediate algebra course in her study, but did not include the same predictors that are in this study. This study does little to address the social integration part of Tinto's theory. A future study addressing the social integration aspect of the theory would be useful in improving the understanding of why students drop out of college and being able to make improvements to help students be successful. Possibly a qualitative study that will also address the social integration aspect of Tinto's Theory of Student Retention would be appropriate.

This study does not take into account the possibility of students retaking the developmental mathematics course of this study. This study could have been improved by taking this into consideration, but this limitation can be taken into consideration for a future study. High school GPA was measured numerically in this study and did not address the fact of a student obtaining a GED. Future studies could include students having a GED and not only a high school GPA. Also, this study did not include data from the year 2020 due to the Covid-19 global pandemic. An investigation of the effects of the Covid-19 pandemic on developmental mathematics and other courses would be valuable. Replicating this study or implementing a similar study at a larger college or university would be beneficial in expanding the existing literature on the topic of this study. Shawnee State University is a smaller institution with a small number of instructors teaching particular courses and thus limiting the variability in instructor characteristics in this study. There was also variability issues with student age leading to the exclusion of that predictor and a study at a larger institution may help with this limitation as well. Since students might be more representative of the Appalachian region due to the location of Shawnee State University, a similar study conducted at an institution of a different location would be beneficial as well.

Summary

Numerous students enter college underprepared for college level courses and required remediation to strengthen their basic skills. Inspired by another study, this study was designed to analyze potential predictors of success in developmental mathematics to help reveal areas of improvement to developmental mathematics courses. The creation of developmental education began years ago when there was a realization of the need for remediation of students and the necessity of allowing any person no matter the background to gain a college education. Studies have shown the importance of implementing developmental education, such as mathematics, in order to help students be successful, however, there does exist studies that contradict those findings. After the analyses of the research questions, ACT math score, pretest, high school GPA, class size, and Pell-Grant status were the 5 predictors that remained in the reduced model after a forward selection logistic regression analysis. Out of the 5 predictors ACT math score, pretest, high school GPA, and class size were statistically significant. This reduced model produced by forward selection logistic regression analysis was an improved model compared to the standard logistic regression model with all the predictors indicated by the AIC and chi-square model comparison. The findings of this study contribute to the existing pool of literature on the topic of this study and also relate to previous findings. Recommendations including a future qualitative study on a similar topic including the social integration aspect of Tinto's theory and conducting a study similar to this one at a larger university to avoid variability issues with some of the predictors were also presented in this chapter.

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Appendix A: IRB Approval

Re: Exempt Review Application Submission

IRB <irb@shawnee.edu>

Mon 11/9/2020 9:44 AM

To: Chelsey Thompson <thompsonc5@mymail.shawnee.edu>
Cc: Douglas Darbro <ddarbro@shawnee.edu>

Good morning, Chelsey and Doug,

I've reviewed your application and agree that it falls under the Exempt category, so you are approved. Good luck with your research.

Sincerely,
Dr. Hamilton

From: IRB <irb@shawnee.edu>
Sent: Friday, November 6, 2020 2:46 PM
To: Chelsey Thompson <thompsonc5@mymail.shawnee.edu>
Cc: Douglas Darbro <ddarbro@shawnee.edu>
Subject: Re: Exempt Review Application Submission

Good evening, Chelsey,

We've received your application and will have it reviewed next week.

Sincerely,
Tim Hamilton
Chairman, IRB

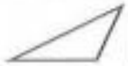
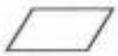
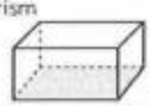
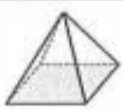
From: Chelsey Thompson <thompsonc5@mymail.shawnee.edu>
Sent: Monday, October 26, 2020 5:39 PM
To: IRB <irb@shawnee.edu>
Cc: Douglas Darbro <ddarbro@shawnee.edu>
Subject: Exempt Review Application Submission

Hello,
My name is Chelsey Thompson and I am submitting an Exempt Review Application for a research proposal. Attached is my Certificate of Completion of the NIH Human Research Participants Training, the Exempt Review Application, and the Research Summary requested in the application.

Sincerely,
Chelsey Thompson

Appendix B: Modified Version of the Wisconsin Mathematics Formula Reference Sheet

Math 0101 Mathematics Formula Reference Sheet

Shape	Formulas for Area and Circumference
Triangle 	Area = ½ (base)(height)
Rectangle 	*Area* = (length)(width)
Trapezoid 	Area = ½ (sum of bases)(height)
Parallelogram 	Area = (base)(height)
Circle 	Area = π (square of radius) *Circumference* = 2π (radius) = π(diameter)
Figure	**Formulas for Volume and Surface Area**
Rectangular Prism 	Volume = (length)(width)(height) *Surface Area* = 2(length)(width) + 2(height)(width) + 2(length)(height)
Cube	Volume = $(\text{side})^3$ Surface Area = $6(\text{side})^2$
Right Circular Cylinder 	*Volume* = $\pi\,(\text{radius})^2\,(\text{height})$ *Surface Area* = $2\pi(\text{radius})^2 + 2\pi(\text{radius})(\text{height})$
Right RectangularPyramid 	*Volume* = $\frac{1}{3}$ (area of base)(height of pyramid)
Right Circular Cone 	*Volume* = $\frac{1}{3}[\pi(\text{radius})^2]\,(\text{height})$
Sphere 	*Volume* = $\frac{4}{3}\pi$ (cube of radius) *Surface Area* = 4 π (square of radius)

Modified from Wisconsin Mathematics Formula Reference Sheet

Appendix C: Math 0101 Course Objectives

Question	Objective
1	Find the perimeter of a polygon.
2	Find the area of a composite shape.
3	Find the perimeter of a composite shape.
4	Find the area of a composite shape.
5	Find the volume and surface area of a solid.
6	Find the length of a side of a right triangle.
7	Find the probability of an event.
8	Solve an equation using the addition principle of equality.
9	Solve linear equations in the form $ax + b = c$.
10	Solve a linear equation using the distributive property.
11	Solve a consecutive odd integer application.
12	Evaluate a formula.
13	Solve an "interest" application.
14	Determine if an ordered pair is a solution to an equation.
15	Solve a compound linear inequality.
16	Find the slope of a line passing through two points.
17	Determine whether lines are parallel, perpendicular, or neither.
18	Write a number in scientific notation.
19	Graph a linear equation by finding and plotting its intercepts.
20	Graph a linear inequality.
21	Use the product rule to simplify expressions.
22	Simplify an exponential expression using more than one rule.
23	Evaluate a function.
24	Simplify a polynomial expression by combining like terms.
25	Add and subtract polynomials.
26	Multiply a binomial times a binomial.
27	Find the square root of a number.
28	Square a binomial.
29	Find the cube root of a number.
30	Find the cube root of an expression.
31, 32	Solve radical equations.
33	Convert from a rational exponent to radical notation.

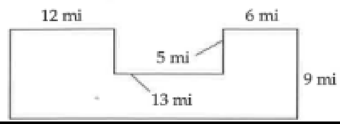
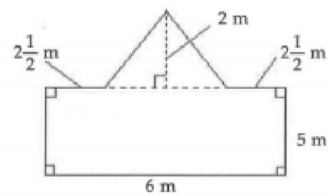
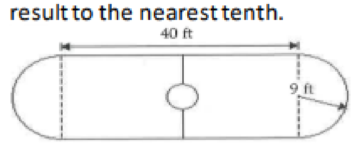
Appendix D: Versons of the Pretest Given in the Semesters of this Study

Academic Term and Test Version	
Spring 2017	C
Summer 2017	C, D, E
Fall 2017	A
Summer 2018	C, D, E
Fall 2018	A, B
Spring 2019	A, B
Summer 2019	A, B
Fall 2019	A, B

Appendix E: Pretest Question Types

Test Format by Version		
Test Version	Number of Questions	Description
A	33	All multiple choice with options A-D
B	33	All multiple choice with options A-D
C	35	Questions 1-31 are multiple choice with options A-D, Questions 32-35 are short-answer response
D	35	Questions 1-31 are multiple choice with options A-D, Questions 32-35 are short-answer response
E	33	All multiple choice with options A-D

Appendix F: Examples of Questions on Pretest

Test-Item Examples	
Test-Item (Intended Component)	Example
1 (Geometry)	Find the perimeter of the figure. 
2 (Geometry)	Find the area of the geometric figure. 
3 (Geometry)	Find the area of the skating rink. If necessary, use $\pi \approx 3.14$ and round your result to the nearest tenth. 
4 (Probability)	A bag consists of 2 red marbles, 8 blue marbles, 5 yellow marbles, and 2 green marbles. What is the probability of choosing a red marble when one marble is drawn?
5 (Linear Equations)	Solve the equation. $0.5x + 0.1 = -0.4$
6 (Linear Equations)	Solve the equation. $5(y+5) = 6(y-7)$
7 (Linear Equations)	The code to unlock a safety deposit box is three consecutive integers whose sum is 69. Find the integers.
8 (Evaluating Equations)	Use the formula $C = \frac{5}{9}(F-32)$ to write 86°F as degrees Celsius.
9 (Linear Equations)	You inherit \$10,000 with the stipulation that for the first year the money must be invested in two stocks paying 6% and 11% annual interest, respectively. How much should be invested at each rate if the total interest earned for the year is to be \$800?
10 (Graphing)	Find the slope of the line that passes through the given points. (-4,5) and (17,10)
11 (Properties of Exponents)	Write the number in scientific notation. 0.000419
12 (Properties of Exponents)	Use the product rule to simplify the expression. Write the result using exponents. $(-9p^5)(-4p^7)$
13 (Evaluating Equations)	If $Q(x) = 2x^2 + 2x - 1$, find $Q(-3)$.
14 (Addition/Subtraction of Polynomials)	Perform the indicated operation. $(3x^2 - 8x + 5) - (x^2 - 5x + 2) + (4x^2 + 5)$
15 (Addition/Subtraction of Polynomials)	Multiply. $(2x - 11)(x + 11)$
16 (Addition/Subtraction of Polynomials)	Multiply. $(3a - 7)^2$
17 (Properties of Radicals)	Find the cube root. $\sqrt[3]{-64x^6}$
18 (Properties of Radicals)	Solve. $\sqrt{5x-1} + 4 = 0$

BIBLIOGRAPHY

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