INFLUENTIAL FACTORS OF ACADEMIC PERFORMANCE AND COURSE RETENTION IN COLLEGE MATHEMATICS: FACE-TO-FACE VERSUS ONLINE

By

Angelique Diane Ramnarine

Elizabeth K. Crawford
Associate Professor
(Chair)

Steven R. Banks
Associate Professor
(Methodologist)

David W. Rausch
Professor
(Committee Member)

John V. Matthews
Professor
(Committee Member)

INFLUENTIAL FACTORS OF ACADEMIC PERFORMANCE AND COURSE RETENTION IN COLLEGE MATHEMATICS – FACE-TO-FACE VERSUS ONLINE

By

Angelique Diane Ramnarine

A Dissertation Submitted to the Faculty of the University of
Tennessee at Chattanooga in Partial Fulfillment
of the Requirements of the Degree of
Doctor of Philosophy

The University of Tennessee at Chattanooga
Chattanooga, Tennessee

May 2018

ABSTRACT

Many lower-level mathematics courses at Tennessee public universities were redesigned in the Fall 2012 semester, after the Complete College Tennessee Act of 2010 eliminated developmental programs from state universities. This study examined the predictive relationships between students' characteristics and their final grades in an entry-level Tennessee college math course that was taught in both online and face-to-face settings. Additionally, the study compared the course grades of students in different learning environments.

The research questions were "Is there a significant, predictive relationship between students' final grades in a math course and their characteristics?"; "How well does the combination of students' characteristics predict academic performance in the face-to-face sections of the math course?"; "How well does the combination of students' characteristics predict academic performance in the online sections of the math course?"; "Is there a statistically significant difference among students' final math grades in different classroom environments, while controlling for ACT math subscores?"

Of the 566 participants, 85.3% and 14.7% were registered in face-to-face and online sections of the math course, respectively. 66.8% of the participants were female, 72.4% were freshmen, 3.2% were considered adult learners, and 70.1% of the students had ACT math subscores below 22.

Multiple regression analyses were used to answer Questions 1, 2, and 3. Multiple linear regression revealed that the standardized residuals for the raw data were not normally

distributed; therefore, a reverse score, logarithmic, transformation was conducted to eliminate the negative skew. Analyses of raw and transformed data values were conducted to improve the predictive validity and credibility of the models' results. Gender and ACT math subscore were consistent, significant predictors of students' grades in the face-to-face sections, whereas ACT math subscore was the only significant predictor of students' final grades in the online sections.

Analysis of variance and analysis of covariance were used to answer Question 4. The results revealed no significant differences in students' grades between the large face-to-face, medium face-to-face, and medium online environments.

This study provides a foundation to assist classroom and departmental educators in decision-making processes, and it assists with understanding relationships between students' characteristics and course outcomes.

DEDICATION

This dissertation is dedicated to my loving parents, Sunnilal and Jane Ramnarine. Many of the opportunities I was fortunate to be provided with are a direct result of their continued sacrifices, encouragement, and love. I will forever be grateful for them.

I also dedicate this dissertation to the memory of my beloved maternal grandmother, Hilda Persaud. My grandmother was orphaned at the age of 3 and lacked the opportunity of an education during the 1930s. Widowed at age 39 and illiterate, her love and dedication to her ten children forced her to work hard to ensure they received the education she was denied during childhood. My grandmother's courage, strength, determination, and perseverance will always be an inspiration to me.

ACKNOWLEDGEMENTS

I believe acknowledgements begin with thanking God. I am blessed. I am thankful that God has been with me and will continue to be with me throughout my professional and personal journeys.

I would like to acknowledge the professional guidance and encouragement received from my Chair and committee members. I sincerely thank Dr. Crawford who served as my professor and Chair throughout the past several years. I greatly appreciate her assistance with the proposal and helpful feedback throughout the dissertation process. I would also like to thank Dr. Rausch, Dr. Banks, and Dr. Matt for sharpening my skills in critical thinking and data analysis. My committee members are leaders and mentors who exemplify the principles and theories emphasized in this doctoral program. In other words, they are life-long learners, transformational leaders, effective educators, and agents who use data and measurement to implement change. I am grateful for the opportunity to have been under their guidance during this process.

TABLE OF CONTENTS

ABSTRACT iv

DEDICATION vi

ACKNOWLEDGEMENTS vii

LIST OF TABLES x

LIST OF FIGURES xii

CHAPTER

I. INTRODUCTION 1

Background of the Problem 2
Statement of the Problem 5
Purpose of the Study 6
Rationale for the Study 6
Importance of the Study 7
Research Questions and Related Hypotheses 7
Theoretical/Conceptual Framework 9
Definition of Terms 11
Methodological/Research Assumptions 14
Delimitations of the Study 14
Limitations of the Study 15

II. LITERATURE REVIEW 16

Introduction 16
Educational Background 17
High School GPA 18
Standardized Exams 19
Demographic Background 21
Age – Nontraditional Students 22
Gender 23
Learning Experience 26
Institutional Mission and Student Resources 27

Classroom Environments 29
Classroom Size 31
Learning Theories 32
Behavioral Learning Theories 33
Information Processing Learning Theories 34
Social Cognitive Learning Theories 35
Constructivist Learning Theories 36
Chapter Summary 37

III. METHODOLOGY 38

Introduction 38
Description of the Population and Sample 38
Variables Analysis 39
Research Design 40
Data Collection 41
Data Analysis 42
Research Questions 43
Chapter Summary 44

IV. RESULTS 45

Refining and Transforming the Data Set 45
Participants 52
Findings 54
Research Question 1 54
Research Question 2 60
Research Question 3 64
Research Question 4 67

V. CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE STUDY 75

Introduction 75
Statement of the Problem 75
Research Questions 76
Summary of the Findings 77
Implications for Further Study 79
Specific Recommendations for This Study and Conclusions 81

REFERENCES 83

VITA 94

LIST OF TABLES

3.1 Variable Analysis..40

4.1 End of Semester Descriptive Statistics of Sample Population by Instructional Design and Gender..53

4.2 Summary of Model for Students' Grades in the Math Course 54

4.3 ANOVA for Final Grades in the Math Course 55

4.4 Coefficients of Predictor Variables for Students' Final Grades in the Math Course..56

4.5 Summary of Model for Transformed Grades in the Math Course...............................57

4.6 ANOVA for Transformed Grades in the Math Course..57

4.7 Coefficients of Predictor Variables for Transformed Grades in the Math Course 58

4.8 Summary of Model for Face-to-Face Students' Grades 61

4.9 ANOVA for Face-to-Face Students' Grades 61

4.10 Summary of Model for Face-to-Face Students' Transformed Grades.......................62

4.11 ANOVA for Face-to-Face Students' Transformed Grades 62

4.12 Coefficients of Predictor Variables for Face-to-Face Students' Grades in Course 63

4.13 Coefficients of Predictor Variables for Face-to-Face Students' Transformed Grades 64

4.14 Summary of Model for Online Students' Grades 65

4.15 ANOVA for Online Students' Grades 65

4.16 Summary of Model for Online Students' Transformed Grades................................65

4.17 ANOVA for Online Students' Transformed Grades 65

4.18 Coefficients of Predictor Variables for Online Students' Grades in Course 66

4.19 Coefficients of Predictor Variables for Online Students' Transformed Grades 67

4.20 Levene's Test of Homogeneity of Variances Using Students' Course Grades 68

4.21 Levene's Test of Homogeneity of Variances Using Transformed Grades 68

4.22 Welch ANOVA Test of Equality of Means for Students' Course Grades 69

4.23 ANOVA for Transformed Grades 70

4.24 Tests of Between-Subjects Effects for Homogeneity of Regression Slopes 72

4.25 Adjusted Means of Course Grades by Instructional Environment With ACT Math Subscore Covariate 74

4.26 ANCOVA Tests of Between-Subject Effects by ACT Math Subscore 74

LIST OF FIGURES

1.1 Theoretical framework for this study identified student characteristics and referenced previous research designs 11

2.1 Inclusive factors influencing student success (Tai et al., 2005; Tai et al., 2006) 17

4.1 Partial regression plot for the assessment of linearity between age and final grade 47

4.2 Partial regression plot for the assessment of linearity between ACT subscore and final grade..48

4.3 Partial regression plot for the assessment of linearity between credits earned and final grade 49

4.4 Scatterplot of the studentized residuals and predicted values.....................................50

4.5 Histogram of standardized residuals and Q-Q Plot of studentized residuals using students final grades in the math course 51

4.6 Histogram of standardized residuals and Q-Q Plot of studentized residuals using transformed grade data..52

4.7 Grouped scatter plot of course grades by ACT math score and instructional design 71

4.8 Assessment of homoscedasticity of the residuals with a scatterplot of the studentized residuals and predicted values in three learning environments...73

CHAPTER I

INTRODUCTION

Over the past decades, one of the main goals for leaders of postsecondary education has been to increase access to higher education for students of various socioeconomic and ethnic backgrounds (Alexander, 2000; Baker & Velez, 1996). This goal has been attained, in part, by Pell Grants, student loans, and various incentives that promote student diversity and access to colleges and universities within the United States (Christensen, Horn, Caldera, & Soares, 2011). Recent data indicate that approximately 20.5 million students were enrolled in U.S. colleges and universities in the fall semester of 2016, which is an increase of about 5.2 million students since fall 2000 (U.S. Department of Education, 2016). According to Hussar and Bailey (2016), from 1998 to 2012 there was a 42% increase in the number of students participating in Title IV federal financial aid programs within U.S. colleges and universities. Additionally, enrollment within post-secondary institutions is projected to continuously increase by 15% from 2012 through 2023 (Hussar & Bailey, 2016).

Although enrollment continues to increase, the graduation rates at many institutions have stagnated in recent years (Christensen et al., 2011). In other words, too few students are graduating on time and many never complete their degrees. According to common college completion metrics data from Complete College America and the National Governors Association, 4% of students complete an associate's degree within 2 years at 2-year colleges, and only 19% and 36% complete a bachelor's degree within 4 years at nonflagship (tier 2) and flagship institutions, respectively (Complete College America, 2013).

Along with reduced graduation rates, the success rates of some gateway courses, including some entry-level mathematics courses, need improvement (Benford & Gess-Newson, 2006; Complete College America, 2012). According to Benford and Gess-Newson (2006), college gateway courses are usually considered to be "large enrollment, entry-level college courses that are prerequisites for majors or graduation" (p. 8). Regardless of age, race, or income, college gateway and remedial courses sometimes become roadblocks for students as they progress through their programs of study (Complete College America, 2012).

Background of the Problem

In 2010, Governor Phil Bredesen led Tennessee in an innovative revision of its model for higher education by signing the Complete College Tennessee Act of 2010 (CCTA). This legislation was based on the guidelines of Complete College America and was supported by a Fund for the Improvement of Postsecondary Education (FIPSE) grant award from the U.S. Department of Education (Complete College America, 2011; Tennessee Higher Education Commission, 2011). "The CCTA calls for a master plan that directs an increase in educational attainment while addressing economic and workforce development, research needs, increased degree production, and increased efficiency through institutional mission differentiation and reduced redundancy" (Tennessee Higher Education Commission, 2011, p. 1). Thus, the Tennessee Higher Education Commission (THEC) developed a statewide master plan that redesigned the curriculum of 45 institutions within the state, to include community colleges and 4-year institutions of the Tennessee Board of Regents (TBR) and the University of Tennessee

(UT) systems (Friedl, Pittenger, & Sherman, 2012; Parker, Bustillos, & Behringer, 2010). The redesign of Tennessee's higher education curriculum included the elimination of remedial courses at 4-year universities. This decision was based, in part, on state and national data regarding student success rates (short- and long-term) and program costs (Complete College America, 2012).

The dilemma surrounding the effectiveness of developmental instruction has been researched for approximately two decades (Li et al., 2013). Noncredit-bearing, remedial courses are intended to increase the mastery of fundamental skills needed for entry-level college courses. Despite the objectives to master necessary and basic skills, institutional and program leaders are often faced with the predicament of placing students in developmental programs with high costs and high attrition rates, rather than enrolling students in course sequences that are associated with higher program completion and graduation rates (Bahr, 2010; Complete College America, 2012; Li et al., 2013). Success and dropout rates are inversely proportional, in that low passing or low student success rates are associated with higher dropout rates. These rates affect the retention rates, graduation rates, and ultimately funding at some universities (Ashby, Sadera, & McNary, 2011; Complete College America, 2012).

In 2012, remedial programs across the United States served approximately 1.7 million beginning students and cost about $3 billion per academic year (Complete College America, 2012). In other words, approximately 40% of first-year college students in 2- and 4-year institutions enrolled in at least one mathematics, writing, or reading remedial course (Belfield & Crosta, 2012; Kowski, 2013). Approximately 55.7% of students who did not take remedial courses at 4-year institutions graduated within 6 years, whereas only 35.1% of students who took remediation courses completed their degrees within 6 years (Complete College America, 2012).

On July 1, 2012, all 4-year institutions governed by the Board of Regents and the University of Tennessee Board of Trustees were required to stop offering remedial and developmental courses in English and Mathematics (Tennessee Higher Education Commission, 2011). The advocates of the CCTA and Complete College America anticipated that the elimination of developmental mathematics in 4-year universities would increase the educational attainment of Tennessee's students, provide continuous progress from 2-year colleges into 4-year universities, and improve the retention and graduation rates at 4-year institutions (Complete College America, 2011). Contrary to these expectations, "anecdotal evidence suggests that students who take foundation courses at community colleges are not always adequately prepared for higher-level courses when they transfer to a 4-year university" (Friedl et al., 2012, p. 1). The contradicting data indicate that factors other than preparation from community colleges and high schools affect student success and graduation rates at 4-year institutions.

The elimination of remedial courses in 4-year institutions generated redesigns for many entry-level college math courses within the affected Tennessee institutions. In some cases, the course redesigns included the removal or reduction of math prerequisite requirements. As a result, the student populations in these courses became more diverse with regard to students' mathematics backgrounds and American College Test (ACT) math subscores. Recent data indicate that 29% of the Tennessee graduating class of 2017 met the mathematics ACT college readiness benchmark of a math subscore equal to 22, down from 30% in 2014, 2015, and 2016 (American College Testing, 2015, 2017b). Since institutions within the TBR and UT systems require undergraduate students to complete at least three credit hours of general education mathematics (Tennessee Board of Regents, 2016; The University of Tennessee, 2016), it would be beneficial for educational leaders to gather and analyze data that may detect relationships among students' final math grades and various student characteristics, to include students' ACT Math subscores. These analyses may assist educational leaders at various hierarchical positions with making better, data-driven decisions that meet the needs of the students and university constituents.

Statement of the Problem

Despite the continued increase of student enrollment in many 2- and 4-year institutions, higher education administrators face economic challenges related to rising institutional costs, stringent government funding formulas, competition among private and public institutions, and limited resources and budgets (Ashby et al., 2011; Christensen & Eyring, 2011; Christensen et al., 2011; Cragg & Henderson, 2013; Hussar & Bailey, 2016). Additionally, the funding formulas for institutions affected by the CCTA are now connected to student performance and progression through programs and degree completion (Complete College America, 2011, 2013). These performance rates are indirectly related to students' success rates in their required 3-hour math courses at TBR and UT institutions.

Success rates in some math courses still need improvement, despite the recent modifications to requirements after the elimination of developmental mathematics at public universities in Tennessee (Complete College America, 2013). Educators teaching redesigned, freshman-level, college math courses with reduced or eliminated prerequisites, are challenged to design and implement courses that support the learning and success of more diversified student populations. An understanding of the relationships that exist between student characteristics and their final grades in their math courses may provide insight for continuous improvement of the course designs and for needed resources to improve student success within the courses and universities.

Purpose of the Study

The overarching goals of this research were to contribute to the body of literature and provide a foundational study toward better understanding the relationships between students' characteristics and their academic performance in a math course. Specifically, the research was designed to identify the predictive relationships between students' characteristics (i.e., predictor variables) and their course grades (i.e., criterion variable) in an entry-level, college math course being taught in online and face-to-face settings. Additionally, the study aimed to identify statistically significant differences between student success rates in the three learning environments of the course: large face-to-face, medium online, and medium face-to-face classes.

Rationale for the Study

It is important for educational leaders to continuously improve the learning environments of their students and targeted audiences (Fitzpatrick, Christie, & Mark, 2009; Mumby, 2013; Rothwell & Kazanas, 2008; Schunk, 2012). Thus, the motivation for this research began with a desire to improve student learning and student success rates in mathematics, specifically in a freshman-level math course redesigned to support a student population with no minimum prerequisite. It is hoped that this research will improve the learning designs and experiences for college math students, while simultaneously meeting the needs of other university stakeholders, instructors and departmental leaders.

Importance of the Study

This study was important for the following reasons. First, the research conducted in this study was designed to contribute to the body of literature related to math education and entry-level college mathematics. The results were intended to provide insight into the general characteristics of students registered in an entry-level, college math course, and to summarize the predictive relationships between students' characteristics and their academic performance in the online and face-to-face sections of the course. Additionally, the results of the study's analyses have the potential to assist leaders in identifying at-risk students and provide educators with data to make decisions that meet the needs of targeted student populations.

Research Questions and Related Hypotheses

The research project focused on the following research questions, null, and alternative hypotheses:

1. Is there a significant, predictive relationship between students' final grades in a math course and their ages, genders, academic ranks (i.e., number of credits earned at the start of the term), ACT math subscores, and classroom environments (i.e., face-to-face and online)?

   $H1_o$: None of the listed characteristics are statistically significant predictors of students' final grades in the math course:

   - Age at the start of the term
   - Gender
   - Academic rank (i.e., number of credits earned at the start of the term)
   - ACT math subscore

- Classroom environment (i.e., face-to-face and online)

H1$_a$: One or more of the listed characteristics are statistically significant predictors of students' final grades in the math course:

- Age at the start of the term
- Gender
- Academic rank (i.e., number of credits earned at the start of the term)
- ACT math subscore
- Classroom environment (i.e., face-to-face and online)

2. How well does the combination of students' age, gender, academic rank (i.e., earned credit hours), and ACT math subscore predict academic performance in the face-to-face sections of the math course?
3. How well does the combination of students' age, gender, academic rank (i.e., earned credit hours), and ACT math subscore predict academic performance in the online sections of the math course?
4. Is there a statistically significant difference among students' final math grades in different classroom designs, while controlling for ACT math subscores?

   H4$_o$*:* There is no statistical difference between students' grades in the three classroom designs: large face-to-face, medium face-to-face, and medium online classes.

   H4$_a$*:* There is a statistical difference between students' grades in at least two of the three classroom designs: large face-to-face, medium face-to-face, and medium online classes.

Theoretical/Conceptual Framework

The theoretical framework of this study was based on the premise that no individual measure is perfect and 100% valid or reliable (Hubbard, 2010; McGrayne, 2011; Patten, 2012). This applies to the measurements used to assess readiness and predict student success in entry-level, college mathematics courses. To better understand possible relationships among student characteristics and their course grades, a data triangulation technique was used to examine multiple cognitive and noncognitive factors related to student success in a college math course (Maruyama, 2012; McGrayne, 2011; Patten, 2012).

Recent data indicate that the majority of students graduating from high schools within the United States are not meeting the widely accepted college readiness thresholds designated by national, state, and institutional leaders (American College Testing, 2012, 2015; Maruyama, 2012). For example, only 28% and 27% of the national graduating classes of 2015 and 2017, respectively, achieved all four college readiness benchmarks on the English, math, reading, and science categories of the ACT exam (American College Testing, 2012, 2015, 2017a). The national benchmark for college readiness in mathematics is an ACT math subscore of 22. The national average of math readiness has steadily decreased from 46% in 2012 to 41% in 2017. More specifically, only 29% of Tennessee high school graduates met the math benchmark in 2017 (American College Testing, 2015, 2017a, 2017b).

College readiness can be defined and determined by different variables and can be confusing to educational leaders, counselors, and students and their families (Maruyama, 2012). For example, although the ACT percentiles indicate that a small proportion of students are fully college ready, university success rates provide data that support a higher percentage of college ready students (Maruyama, 2012). Other measurements of college readiness are high school grade point averages (GPAs) and detailed high school transcripts. These measurements arguably provide better insight into the academic backgrounds and activities of high school students (Belfield & Crosta, 2012; Chew, Knutson, & Martini, 2014). Recent studies indicate that high school grades often serve as better predictors of college readiness and success than ACT scores, and some studies have established positive correlations with high school GPA and first-year college success (Belfield & Crosta, 2012; Chew et al., 2014; Maruyama, 2012; Wilford, 2009). However, high school GPA values are based on inconsistent expectations and requirements of different high schools and teachers (Marsh, Vandehey, & Diekhoff, 2008). According to Maruyama (2012), it is important for educational leaders to collectively determine an appropriate definition for "readiness" and the suitable thresholds that will be used to measure and determine whether students are ready for a particular aspect of college (e.g., graduation, first-year retention, second-year retention, or success in a particular course).

For the purposes of this study, student readiness for a college-level math course was defined through the final grade earned in the specific freshman-level mathematics course (i.e., academic performance in the course). The dependent variable for this research project was the course grade, and the independent variables were cognitive and noncognitive student characteristics. The student characteristics selected for this study were chosen based on the pertinent literature of previous studies and my informed priors. They were identified within three inclusive categories of influential factors for student success: demographic background, general education background, and learning experiences (Tai, Sadler, & Loehr, 2005). Specifically, the independent variables of this study were: age; gender; academic rank (i.e., earned credit hours at the start of the term); class environment (i.e., face-to-face, online, and class size); and ACT math subscore. Inferential statistics were used to establish differences and relationships among the predictor variables and response variable in the sample population. Figure 1.1 summarizes the theoretical framework for this research proposal.

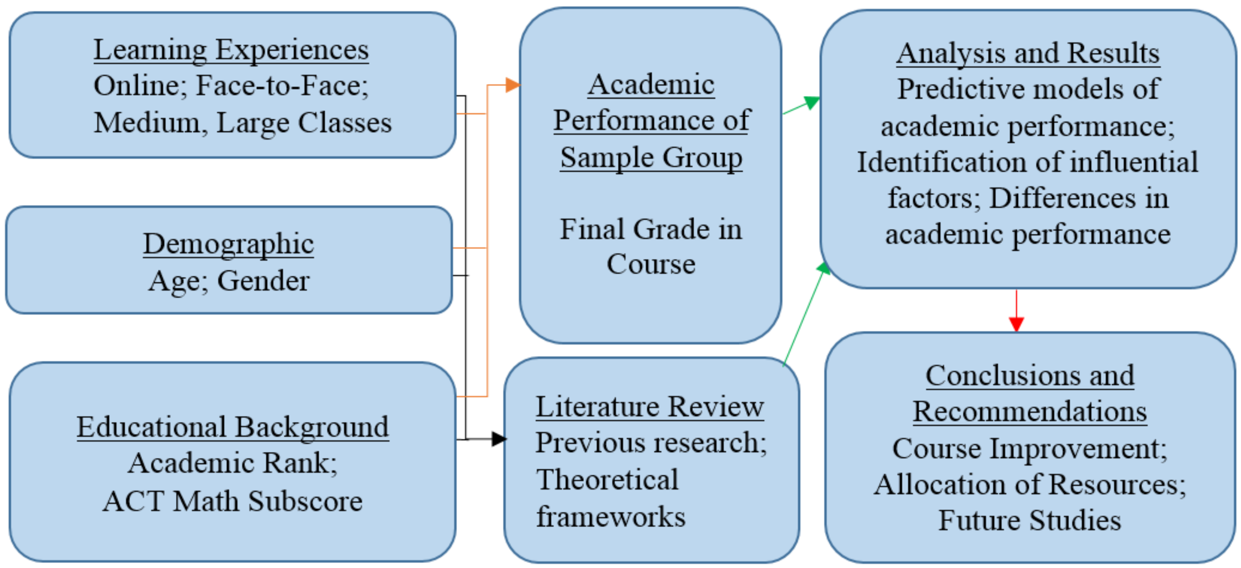

Figure 1.1 Theoretical framework for this study identified student characteristics and referenced previous research designs

Definition of Terms

The following terms are defined to provide readers with a better understanding of the study's focus and findings.

- Adult learner: A subgroup of students classified within the nontraditional college student cohort who are commonly 25 years or older (Pelletier, 2010). For the purpose of this research, age was the simple criterion used to differentiate a nontraditional student, adult learner, from a traditional college student (Council for Adult and Experiential Learning, 2005).
- College readiness: "The level of preparation a student needs to enroll and succeed in a college program (certificate, associate's degree, or baccalaureate) without requiring

remediation" (Venezia & Jaeger, 2013, p. 118). For the purpose of this research study, college readiness referred to to the level of preparation needed to successfully earn an A,B, or C in an entry-level, math course with no prerequisite requirements.

- Distance Learning: A form of instruction that is commonly interchanged with online, web-based, e-learning, and distance education. Distance education "describes the effort of providing access to learning for those who are geographically distanct" (Moore, Dickson-Deane, & Galyen, 2011, p. 129). Distance learning occurs between two parties, a learner and an instructor, and occurs remotely at different times and/or places using various forms of electronic communications and instructional materials (Moore et al., 2011).
- Earned credit hours: Credit earned for successfully completing the requirements of a collegiate course (Purdue University, n.d.). For the purpose of this study, the earned hours reported corresponded to the accumulated credit hours for semesters prior to the term students were enrolled in their college math course. Based on the earned credit hours, students were identified as freshmen (0-29.9 hours), sophomores (30-59.9 hours), juniors (60-89.9 hours), and seniors (90+ hours).
- Face-to-Face (F2F) course: "Traditional classroom environment where the instructor and the students are not separated by geographic space or time" (University of Tennessee at Chattanooga, 2016b). For the purpose of this study, a face-to-face course referred to classes that met for 50-minutes, three times per week.
- Gateway college courses: "Large enrollment, entry-level college courses that are prerequisites for majors or graduation" (Benford & Gess-Newson, 2006, p. 8).

- General education mathematics course: A mathematics course at a 4-year institution that meets the general education requirements and academic standards set forth by the specific institution of higher education (Kirst & Venezia, 2001).
- Nontraditional college students: Students who meet one or more of the following criteria: work full-time while enrolled in college courses, 25 years or older, attend college part-time, do not have a standard high school diploma (i.e., earned a General Educational Development (GED) credential), have one or more dependents, single parents (Council for Adult and Experiential Learning, 2005; Pelletier, 2010; U.S. Department of Education, 2015b).
- Online course: Definition varies per institution. For the purpose of this research, an online course was defined as one in which online content replaced at least 80% of the traditionally required attendance or participation in a face-to-face course (I. E. Allen, Seaman, Poulin, & Straut, 2016). For example, in a three-credit hour class, there was no more than 9 required face-to-face hours for campus attendance or in-person/proctored tests (University of Tennessee at Chattanooga, 2016b).
- Traditional college students: Students who do not have the aforementioned characteristics of nontraditional college students (Council for Adult and Experiential Learning, 2005; U.S. Department of Education, 2015b).
- Student success: "The ultimate measure of college readiness and of productive remedial education is success in first-year, college-level gateway courses" (Complete College America, n.d., p. 5). For the purpose of this report, success was associated with the final grade earned by a student in the entry-level college math course. Specifically, student success was identified with the final letter grades A, B, and C.

- Student learning: Student learning can be assessed through formative and summative instructor-based assessments. However, for the purpose of this study, student learning was measured using the final grades that are permanently recorded in the students' transcripts. Final grades are considered to be more significant than classroom assessments (Tai, Sadler, & Mintzes, 2006).

Methodological/Research Assumptions

I made several assumptions within the design and implementation of this quantitative study. If alternative assumptions are presumed, future results could be different. The following assumptions were made for this study:

- I, the researcher, controlled for bias.
- Student learning is measurable and can be represented by students' grades.
- The face-to-face and online classes had the same or comparable course objectives and requirements. For example, students were required to complete the same homework, quiz, test, and final exam assessments.
- The gathered data from the University's learning management system and official student records were reliable, valid, and accurate.
- No students were simultaneously registered in both sections of this course or repeated the course during the specified semesters.

Delimitations of the Study

The methodology and findings of this study may lack generalizability because of the following delimitations:

- The study's results are delimited to data from students registered in one general education math course within the university. A student's grade in his/her math course is only one of many factors affecting the overall performance within the institution.
- The study's results are delimited to five predictor variables, which do not represent all of the influential factors related to student success.
- The study's results are delimited to the age characteristic of nontraditional students.
- The study's results are delimited to students who had a recorded ACT math subscore in their institutional records.
- The study's results are delimited to data gathered from classes taught by one instructor during two academic years.

Limitations of the Study

The methodology and findings of this study may lack generalizability because of the following limitations:

- The study's results are limited to data gathered from one public, metropolitan university in a southeastern state of the United States.
- The study's results are limited to data collected by one instructor who was also the researcher for this study.
- The study's results are limited to data from students who self-registered (i.e., self-selected) into the course sections (i.e., online, large face-to-face, medium face-to-face classes).

CHAPTER II

LITERATURE REVIEW

Introduction

Financial aid incentives for higher education have widely increased the diversity of students' demographic and educational backgrounds (Horn, Peter, Rooney, & Malizio, 2002). Data indicate that although the population of undergraduates has broadened, the graduation rates for postsecondary degrees have decreased (Christensen et al., 2011; Complete College America, 2012; Horn et al., 2002). University educators are responsible for designing and implementing learning environments that meet the needs of their targeted students (Rothwell & Kazanas, 2008), and they must now determine solutions for accommodating students with a higher risk of attrition (Horn et al., 2002; Li et al., 2013). Influential factors of success can be grouped into three inclusive categories: demographic background, general education background, and learning experiences (Tai et al., 2005). Figure 2.1 provides a Venn diagram of this concept, which corresponds to the study's theoretical framework (Figure 1.1).

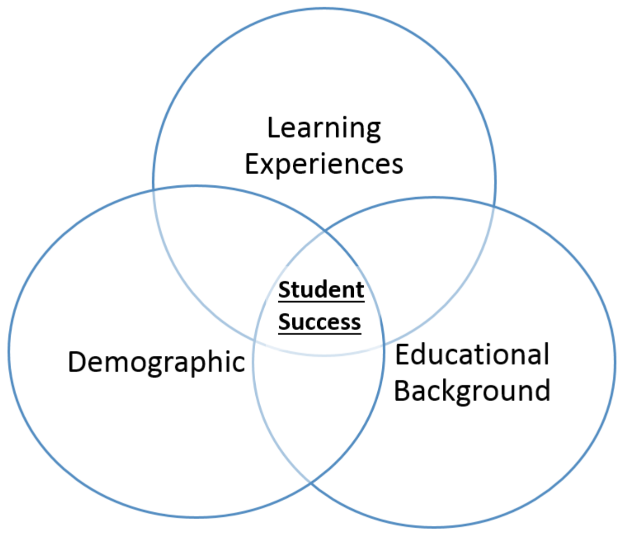

Figure 2.1 Inclusive factors influencing student success (Tai et al., 2005; Tai et al., 2006)

Indicators of social circumstance, demographic background, and prior academic achievement, general education background, are interconnected with learning environments and success during students' educational experiences at college (Tai et al., 2005). The following review of pertinent literature provides insight into the inter connection of factors associated with students' demographics, general education backgrounds, and learning experiences within their institutions of higher education.

Educational Background

Past academic achievement is one of the factors considered in the evaluation and admissions processes of potential students (Kobrin & Patterson, 2011; Marsh et al., 2008; Maruyama, 2012; Parker et al., 2010; Sackett, Kuncel, Arneson, Cooper, & Waters, 2009; Schauer, Osho, & Lanham, 2011). During the decision process, admissions officers are responsible for deciding whether potential students are ready for college-level work at their institutions. Additionally, instructional and departmental leaders must determine the prerequisite requirements that are used to judge the readiness of students for particular courses. College or course readiness are often measured on the assumption that the students' standardized test scores on the American College Test (ACT) and Scholastic Aptitude Test (SAT) or high school grade point averages (GPAs) are accurate reflections of students' academic understanding.

High School GPA

Research studies provide varying results regarding the relationship between high school GPA and college success. Some studies provide evidence of significant relationships between first-year retention, college success, and high school performance (Belfield & Crosta, 2012; Chew et al., 2014; Wilford, 2009). For example, Chew et al. (2014) noted that when high school GPA was used as a predictor variable for first-year college success, approximately 48.1% of the students flagged with high school GPA concerns had negative retention indicators (NRI). These NRIs included dropping out of the institution, infrequently attending their courses, and being placed on academic probation (Chew et al., 2014). Additionally, high school GPA was shown to have a strong association with college credit accumulation and college GPA (Belfield & Crosta, 2012). Belfield and Crosta (2012) also noted that students' college GPAs are less than 1 unit below their high school GPAs.

Other studies indicated that students' high school GPAs are not good predictors of college success because high school grades are sometimes inflated due to a lack of standardization among grading scales and expectations (Bromberg & Theokas, 2016; Marsh et al., 2008; Maruyama, 2012; Sawyer, 2013). In other words, some secondary schools "do a poor job of preparing their students for college" (p. 712), and students are simply not ready for college level work (Zimmerman, 2014). Many high school administrators are faced with addressing course failure rates that not only affect their schools' completion rates and course outcome reports, but also students' self-perception, motivation, and efficacy (Bromberg & Theokas, 2016). This situation is complicated and often results in credit recovery programs that place priority in credit accrual with an end goal of simply matriculating from high school. When this happens, students are often not prepared for college or a career (Bromberg & Theokas, 2016).

Over the years, many college administrators have begun to take a closer look at students' high school transcripts, rather than only their high school GPA (Adelman, 2006; Bromberg & Theokas, 2016; Hagedorn & Kress, 2008). The consideration of both high school GPA and an examination of high school courses, provides a proxy for a range of attributes such as effort, cognitive competence, and college-level readiness (Adelman, 2006; Belfield & Crosta, 2012). For example, students who took advanced course sequences or math courses beyond algebra II in high school had an increased likelihood of being college ready and completing a bachelor's degree (Adelman, 2006; Bromberg & Theokas, 2016). While transcript analysis has been shown to be beneficial at identifying college-ready students, it is still not perfect. Bromberg and Theokas (2016) reported that approximately 14.2% of high school graduates who completed a cohesive curriculum (i.e., sequence of courses aimed to prepare students for college or a career) were unable to demonstrate mastery of that curriculum. This indicates that "seat time [or completion of a cohesive curriculum] is not sufficient to signify readiness for a postsecondary learning opportunity" (Bromberg & Theokas, 2016, p. 8).

Standardized Exams

Regardless of students' educational backgrounds (e.g., high school size, attendance at a public or private school, or being homeschooled), it is generally accepted that ACT or SAT standardized test scores provide a nationally-normed criterion for college readiness (Scott, Tolson, & Huang, 2009). In Tennessee, the ACT is the dominant college admission test, meaning that “more than half of the students elect to take that test” (Southern Regional Eduation Board, 2007, p. 1). In fact, under current Tennessee law, every 11th grade student enrolled in a public school is required to take the ACT (Tatter, 2015). The ACT college readiness benchmark for mathematics is a score of 22. With this score, students are estimated to have a 50% chance of obtaining at least a B or a 75% chance of obtaining a minimum grade of a C in a credit-bearing college course, such as college algebra (American College Testing, 2014). In 2015, 42% of the nation’s ACT-tested high school graduates met the college readiness benchmark for mathematics (American College Testing, 2015). This percentage reflects an 8.69% decline in the national percentage of students meeting the college readiness benchmark for mathematics from 2012 (American College Testing, 2015). In 2015, only 30% of high school graduates in Tennessee met the college readiness benchmark in mathematics (American College Testing, 2015).

Standardized test scores have been used for decades to predict success in college, however, recent studies indicate that these scores alone are not sufficient in predicting college success (Marsh et al., 2008; Maruyama, 2012; Sackett et al., 2009; Schauer et al., 2011). Critics of standardized tests assert that the “multiple-choice questions on college entrance examinations are artificial and do not represent the types of tasks that college students undertake in their coursework” (Kobrin, Kim, & Sackett, 2012, p. 111). Furthermore, regression analyses for state and national data indicate weak and unclear predictive relationships between standardized test scores and final grades in first-year college math courses (Jenkins, Jaggars, & Rokso, 2009; Maruyama, 2012). Belfield and Crosta (2012) generalized that standardized test scores were better at predicting which students would do well (i.e., earn higher college grades) rather than those who would satisfactorily pass their college courses (i.e., earn average grades).

Many institutions of higher education in the United States currently use both standardized tests scores and high school GPA on admission and financial aid decisions (Kobrin & Patterson, 2011; Scott et al., 2009; Sparkman, Maulding, & Roberts, 2012). University leaders who use both high school GPA and standardized admission test scores have a better chance of predicting student success than those who consider either variable alone (Marsh et al., 2008; Maruyama, 2012; Scott et al., 2009; Sparkman et al., 2012). Studies also indicate that universities that select students based on standardized admission test scores and high school GPA, rather than only one variable, can expect higher retention rates and success from students (Marsh et al., 2008; Scott et al., 2009).

This study considered only ACT math subscores as one of the predictor variables of student readiness and success. The rationale for this decision was twofold. First, high school GPAs are not consistently determined by the same standards or scales. "GPAs produce valid comparisons across students only if the course demands and teacher standards are either constant or randomly distributed across courses" (Bailey, Rosenthal, & Yoon, 2014, p. 1). Secondly, the ACT and SAT exams are graded on different scales. Therefore, out of convenience, I utilized only ACT math scores, which was the primary standardized test for the state in which this study was conducted.

Demographic Background

Although high school GPA and standardized test scores are used in the college admissions process, inconsistencies among studies indicate that noncognitive and nonacademic characteristics (i.e., demographic characteristics) may influence the attainment of success in college programs and college-level courses (Maruyama, 2012; Tai et al., 2006). Demographic factors provide data on socioeconomic variables that reflect differences between advantaged and disadvantaged college students, race and ethnicity, and highest parental education levels (Tai et al., 2006). For the purpose of this study, I focused on two demographic characteristics: gender and age.

Age – Nontraditional Students

The student population among U.S. universities and colleges continues to diversify and expand not only with incoming freshmen, who are often considered to be traditional college students, but also with nontraditional college students. Nontraditional students are often older, returning to school, commuting to and from campus, and/or working full- or part-time (Kulavic, Hultquist, & McLester, 2013). According to Pelletier (2010), “data reported by the consulting firm Statmats suggests that as few as 16 percent of college students today fit the so-called traditional mold: 18- to 22- years old, fully dependent on parents, in college full-time, [and] living on campus” (p. 2). In other words, traditional college students are now the exception, rather than the norm (Council for Adult and Experiential Learning, 2005; Pelletier, 2010; U.S. Department of Education, 2002, 2015b). Much of the current literature focuses on traditional college students (Chao & Good, 2004; Kulavic et al., 2013), and although these studies are relevant within today’s universities, it is also important to consider the constantly changing needs and preferences of the approximately 6.8 million nontraditional students enrolled in colleges and universities across the United States (Kulavic et al., 2013).

Data over recent decades indicate that at least 70% of all undergraduate students in U.S. colleges and universities meet at least one of the characteristics of a nontraditional student, therefore, making nontraditional students the majority of students registered in today's college courses (Council for Adult and Experiential Learning, 2005; U.S. Department of Education, 2002, 2015b). Although nontraditional students can be identified by several characteristics, these students are commonly classified by the simple criterion of age, and are considered to be nontraditional, adult learners when they are 25 and older (Council for Adult and Experiential Learning, 2005; Pelletier, 2010).

This research study utilized retrospective data from institutional records. Due to the limitations of the available data, traditional and nontraditional students were identified only by their ages. Since this study focused on students registered in an entry-level math course, it was determined that less than 5% of the sample population of students were adult learners. This disproportion will limit the generalizability of results with regard to students' ages and academic performance in the course.

Gender

Previous studies have produced controversial results about the quantified impact or relationship that gender has on students' performances in specific subject areas and instructional learning environments (Arnold & Rowaan, 2014; Halpern, Straight, & Stephenson, 2010; Skaalvik, Federici, & Klassen, 2015; Voyer & Voyer, 2014; Wladis, Conway, & Hachey, 2015; Xu & Jaggars, 2014). "The empirical literature on cognitive gender differences reveals that males and females exhibit different average levels of performance on many, but not all, cognitive tasks" (Halpern et al., 2010, p. 337). For example, one of the most consistent finding is that males generally outperform women on several measures of visuospatial performances, which are often associated with topics pertaining to math and science and include line orientation, mental rotation, complex figure drawing, and abstract inferences (Guerrieri et al., 2016; Halpern et al., 2010; Tversky, 2005). Another consistent finding among empirical studies is that writing achievements and grammar skills are typically higher among females (Halpern et al., 2010; Lee, 2013). Despite the differences among male and female abilities, Tversky (2005) noted that :

> Spatial ability does not contrast with verbal ability; in other words, someone can be good or poor at both, as well as good in one and poor in the other. In addition, spatial ability (like verbal ability) is not a single, unitary ability. (p. 216)

Tversky's assertion can be related to social cognitive learning theory and self-efficacy, which has a broad utility and can be used to understand psychological differences (Hyde, 2014; Skaalvik et al., 2015; Tversky, 2005). According to Bandura (1977), self-efficacy is defined as "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (p. 193). Studies have shown that the differences in self-efficacy between genders vary by the academic subject and the age of the individuals (D'Lima, Winsler, & Kitsantas, 2014). Skaalvik et al. (2015) further explained the concept of self-efficacy to be students' beliefs about their abilities (i.e., "Can I do this task?"), as opposed to self-concept that addresses the level of skills and abilities students' think they possess (i.e., "Am I good at this task?"). Although Skaalvik et al. (2015) did not establish significant differences in grades with respect to gender, however, they noted that "boys had significantly higher mathematics self-efficacy compared to girls", which seemed consistent "with a gender stereotype perspective where mathematics is perceived as more suited for males than for females" (p. 135).

Students who expect that they will perform poorly on math-related material are more likely to perform worse than those who think positively of their abilities (Jozkowskia, Malhotra, Shapero, & Sizoo, 2008; Skaalvik et al., 2015). Klassen, Krawchuk, and Rajani (2008) echoed these assertions with data from two studies that provided evidence linking self-efficacy with motivation, procrastination, and academic performance. The authors noted that the most predictive self-reported variable of procrastination was self-efficacy for self-regulation (Klassen et al., 2008). Students who self-reported that procrastination negatively influenced their academic performance also reported having a lower self-efficacy to self-regulate their tasks, which resulted in more procrastination time and lowered expectations for course grades (Klassen et al., 2008).

The effect of gender stereotype perspectives on self-efficacy often affects the types of occupations in which students believe they can succeed (Bandura, Barbaranelli, Caprara, & Pastorelli, 2001). Data from the National Center for Education Statistics (NCES) provide insight into the number and percentages of science, technology, engineering, and mathematics (STEM) degrees/certificates in postsecondary education. According to the NCES (U.S. Department of Education, 2015a), approximately 30.9% of the 603,992 total STEM degrees and certificates conferred to U.S. citizens and nonresident aliens in 2013-14 were awarded to females. Similarly, of the 318,667 STEM Bachelor's degrees conferred to U.S. citizens and nonresident aliens in 2013-14, 35% were awarded to female students. These data allude to the possibility that gender stereotype perspectives still exist within our society and educational expectations. This research study examined whether gender was a significant predictor of academic performance in the entry-level math course.

Learning Experience

Self-regulated learning (SRL) and cognitive transfer of skills and knowledge are essential components for success in both face-to-face classrooms and online learning environments (Barak, Hussein-Farraj, & Dori, 2016). The concept of self-regulated learning (SRL) refers to the learner's ability to use the appropriate strategies that positively impact his/her learning. These strategies include resource management, motivation, cognition, and metacognition. Cognitive transfer is the ability to function in a new situation according to what one has learned in a previous situation (Barak et al., 2016). The educational environments and designs that educators provide to undergraduate students, particularly to student populations experiencing academic problems and high failure rates, should not only include assistance to complete assignments, but should also provide resources that build students' confidence in implementing both cognitive and metacognitive strategies for academic success (Klassen et al., 2008).

Low self-efficacy impacts the choices students make in regard to effort, persistence, procrastination, and achievement (Bandura, 2011; Bandura et al., 2001; Klassen et al., 2008; Skaalvik et al., 2015). According to Bandura et al. (2001), perceived self-efficacy affects adaptations, aspirations, commitments, levels of motivation and persistence, and vulnerability to stress and depression. More specifically, students' self-efficacy in mathematics influences their perceptions of their abilities to perform math-oriented tasks (Jozkowskia et al., 2008; Skaalvik et al., 2015). Low self-efficacy often results from negative experiences and environmental factors, including failed performances or negative reactions from parents or teachers (Bandura et al., 2001; Hall & Ponton, 2005; Klassen et al., 2008; Schunk, 2012; Woodard, 2004). According to Klassen et al. (2008) students who procrastinate with course assignments often delay starting the right tasks and devote too much time to the wrong tasks. In other words, "procrastinators have difficulties with *tactics* (organizing and maneuvering resources for a short-term goal)…, [and] also with *strategy* (carefully devised plan of action to achieve long-term success)" (Klassen et al., 2008, p. 927). This assertion indicates that many students need assistance in cognitive and metagonitive strategies to improve their self-efficacy, motivation, and chances for success. Cognitive strategies are implemented to promote cognitive progress, whereas metacognitive strategies monitor progress. These types of strategies are not disjoint, but can be used to achieve both cognitive and metacognitive knowledge (Barak et al., 2016; Flavell, 1979).

This research study focused on a freshman-level math course taught in large and medium face-to-face classrooms and medium online learning environments. The course designs were comparable and required students to demonstrate competency of the same learning objectives. The following section of this review expounds upon the literature from previous studies pertaining to the learning environments in higher education.

Institutional Mission and Student Resources

Universities and colleges are often viewed as being more effective and efficient when retention and graduation rates are high because these rates are strongly correlated with more academically qualified students (Cragg & Henderson, 2013). The retention and graduation rates are often directly related to an institution's mission, which are usually in agreement with the institution's culture (Fjortoft & Smart, 1994). The allocation of institutional funding should be judged against the mission and should be responsive and reflective of current external factors and uncertainties (Ashby et al., 2011; Fjortoft & Smart, 1994; Krumrei-Mancuso, Newton, Kim, & Wilcox, 2013; Malm, 2008; Schloss & Cragg, 2013). In other words, a university's culture, tradition, and values should be reflected in the prioritized funding of resources provided to university constituents, particularly in their learning environments. Educational leaders are responsible for providing learning experiences that continuously support the success of their students and the missions of the institution (Krumrei-Mancuso et al., 2013; Rothwell & Kazanas, 2008).

A major problem identified within many of today's postsecondary institutions is that most college freshmen in the United States are not 'college ready' and lack the prerequisite skills for many college-level courses, to include entry-level mathematics courses (American College Testing, 2012). Additionally, many freshmen enter college with negative mindsets toward the subject matter and these "poor attitudes often translate into poor engagement with the course, which inevitably leads to failure" (Mayes, Chase, & Walker, 2008, pp. 28-29). It is important for institutional leaders to remember that learning environments and resources for student success should be designed to meet their targeted students' academic and nonacademic needs (Rothwell & Kazanas, 2008). In other words, educational leaders are responsible for not meeting the short- and long-term missions of their institutions, but also providing learning experiences that continuously support the success of their admitted students (Krumrei-Mancuso et al., 2013).

Provided support affects the stability and continuity of students and institutions (Simplicio, 2012). For example, the mission statement of the College of Arts and Sciences at the university for which this study took place, states that the College's first priority is effective instruction and that the College supports the University's efforts to support diverse opportunities and wide access to higher education (University of Tennessee at Chattanooga, 2016a). This mission is partly met through the enhancement and improvement of student resources in face-to-face and internet-based courses. Supportive elements that institutional leaders control are class size, frequency of meetings, tutoring services, and face-to-face or online resources (Tai et al., 2005). This study aims to better understand the relationships and differences among student characteristics and their grades in various types of classrooms. In turn, these results may assist educators in making data-informed decisions that not only meet the institution's goals and budgets, but that also efficiently meet the needs of the targeted students within the math course.

Classroom Environments

Traditional universities have utilized lecture style courses and research-based mentalities for decades; however, they must now determine ways to compete with newer, less established institutions that have demonstrated organizational success with increasing rates of student enrollment and degree-completion (Christensen & Eyring, 2011; Christensen et al., 2011; Cragg & Henderson, 2013). From 1980 to 2008, the number of public and for-profit degree granting institutions increased by 48% and 500%, respectively (Cragg & Henderson, 2013). One reason why the smaller, for-profit universities have been successful is because of their aggressive adoption and implementation of online and distance learning strategies. The growth of for-profit institutions also coincides with the growth of online learning (Christensen et al., 2011). The development of the internet and online learning has recently ended "an anomalously long run of disruption-free growth" in the higher education industry (Christensen & Eyring, 2011, p. 18).

Online courses are appealing to many college students and institutional leaders because they offer greater convenience, have a lower institutional cost, and allow institutional leaders to easily assess teaching performance and make needed improvements (Barak et al., 2016; Christensen & Eyring, 2011). According to Christensen and Eyring (2011), if online instruction is appropriately designed with well-defined learning outcomes, then the "online instructor's teaching performance is easily monitored" (p. 214). Thus, quality enhancement of courses and programs throughout the institution could be improved and observed. Online courses also have a lower instructional cost and are more manageable for students who are in various stages of their careers (Christensen et al., 2011). An improvement in availability to university courses could expand the student body of the institution without the large costs associated with new buildings and full-time faculty (Christensen & Eyring, 2011). Lower costs and a rise in enrollment provide the institution with increased revenues and decreased costs during a time when institutional funding is harder to establish (Ashby et al., 2011; Christensen & Eyring, 2011).

Compared to face-to-face lecture courses, appropriately designed online courses have the potential to better service today's broad student population because online courses provide flexibility (Prensky, 2006). Students who enroll in online courses may be traditional on-campus students, sometimes referred to as "digital natives" (Prensky, 2006, p. 8); nontraditional students; and distance learners. According to Rothwell and Kazanas (2008), "learners before the so-called digital divides are generally less comfortable with online learning experiences than younger people [digital natives], who grew up with it" (p.110). It is important for educators to assess whether the instructional design of an online course provides appropriate instructions and resources for students with varying levels of comfort and experience in the online learning environment (Rothwell & Kazanas, 2008). An effective design for face-to-face and online math courses should not only be based on the content-related requirements of the institution's curriculum, but also on analyses pertaining to students' characteristics and needs (Rothwell & Kazanas, 2008).

Classroom Size

Studies pertaining to classroom size and student success have been conducted since 1900 and one reason why the issue of class size continues to be a topic of concern is because of the tensions between research findings and the cost of implementation (Biddle & Berliner, 2015; Miles & Ferris, 2015). Much of the research indicates that a reduced class size, particularly with less than 20 students per 1 teacher, positively affects the short- and long-term achievement of students (Biddle & Berliner, 2015; Schanzenbach, 2014, 2016). Schanzenbach (2016) cautioned that a simple correlation between class size and student achievement is confounded by many other factors. For example, in many institutions low-achieving or special needs students are systematically assigned to smaller classrooms so that they receive extra interactions with their instructors. "A simple correlation in this case would find class size to be positively associated with achievement" (Schanzenbach, 2016, p. 60). This type of simple correlation could not be validly generalized to indicate that class size impacts student success because the correlation is biased by other omitted variables, such as special needs status (Schanzenbach, 2016). Due to research limitations, correlational analyses sometimes indicate that there are no statistical relationships or no positive relationships between class size and student achievement. In such cases, researchers conclude that since student success cannot be guaranteed, class size does not matter (Biddle & Berliner, 2015; Schanzenbach, 2016).

Research also indicates that class size impacts the emotional and instructional support that students receive within their classrooms (J. Allen et al., 2013). "Measured emotional and instructional support in the classroom was of greatest predictive value for student academic achievement in smaller as compared to larger classrooms" (J. Allen et al., 2013, pp. 86-87). This corresponded to the observations of Miles and Ferris (2015), who indicated that instructors who are responsible for 100+ students do not usually develop strong personal relationships with their students. Learning not only happens through vicarious and enactive learning techniques, but through student-student and teacher-student relationships (Miles & Ferris, 2015; Schunk, 2012). This concepts can be related to the motivational factors affecting student cognitive and metacognitive skill levels within a course (Bandura, 2011; Flavell, 1979; Klassen et al., 2008; Skaalvik et al., 2015). Thus, the consideration of learning theories reflected within classroom activities are also important concepts in understanding the possible relationship between instructional environments and student performance.

Learning Theories

"Mathematics teachers' beliefs have an impact on their classroom practice, on the ways they perceive teaching, learning, and assessment, and on the ways they perceive the students' potential, abilities, dispositions, and capabilities" (Barkatsas & Malone, 2005, p. 71). These beliefs about teaching and learning are often changed by instructors' valued outcomes (i.e., student learning) and classroom practices and trials (Barkatsas & Malone, 2005; Nisbet & Warren, 2000). While experiences and empirical observations are useful in helping to improve educators' beliefs and instructional practices, "theory and research are [also] integral to the study of learning [and improvement]" (Schunk, 2012, p. 10). A single theoretical framework for learning should not be used to design or guide the instructional strategies implemented in a classroom because situations with humans are unique to the individuals and the specific situation (Mumby, 2013; Northouse, 2010; Rogers, 2003; Schunk, 2012). The activities implemented in learning environments (e.g., face-to-face and online courses) of various class sizes (e.g., small, medium, and large) should provide evidence of an understanding that student success is influenced by variables in the three inclusive categories: demographic background, general education background, and learning experiences (Tai et al., 2005). The subsequent part of this review provides a summary of relevant learning theories within the instructional design of a college course.

Behavioral Learning Theories

Behavioral learning theories place emphasis on environmental factors and the influence these factors have on the individuals within the learning environment (Schunk, 2012; Swan, 2003). Instructional strategies that utilize these theories are practical, and even inevitable (Schunk, 2012). For example, instructors often use direct instruction to model tasks, ask students to practice independently, and then provide feedback. Students may learn the task as a response to the instructions and demonstrations provided by the instructor. The associations learned by the students are central to learning and are created through interactions with content, instructors, and peers (Swan, 2003). Thorndike (1913) asserted that "learning is connecting" (p. 55), and successful teaching involves connections between previously learned information and new material. Students' chances for success are affected by teaching strategies that provide appropriate time to learn the material, both inside and outside the classroom.

These strategies allow students to make connections to previously understood concepts, while practicing and mastering the new concepts. For example, activities such as formative assessments, help educators check for understanding by promoting trial and error practice that reinforce concepts and eliminate misconceptions (Schunk, 2012). In the face-to-face and online learning environments, instructors should create assessment-centered designs to gather data that check student progress through meaningful, formative assessments (Gikandi, Morrow, & Davis, 2011). Examples of these types of assessments include: independent practice questions, discussion forums, and self-test quiz tools.

Information Processing Learning Theories

"Information processing theories focus on attention, perception, encoding, storage, and retrieval of knowledge" (Schunk, 2012, p. 224). Retrieval of knowledge triggers associations in a person's memory by activating and recalling relevant knowledge needed to implement a new action (Schunk, 2012). The information processing model is applicable in online and face-to-face math courses because students are required to retrieve information from their long term memory (LTM) to assist with learning new concepts. "Information that is meaningful, elaborated, and organized is more readily integrated into LTM networks" (Schunk, 2012, p. 202). Lesson plans that incorporate graphs, tables, Venn diagrams, and other clearly presented illustrations assist students in visualizing and understanding concepts, and link new information with knowledge already in their memory (Schunk, 2012). These illustrations also reduce the extrinsic cognitive loads of students, which is critical in developing effective cognitive schemas that support the learning of new concepts. Learning opportunities are reduced when students dedicate their limited mental resources to extrinsic rather than intrinsic cognitive needs (Schunk, 2012). Other useful techniques are molding and scaffolding, which assist learners with mastering skills that they would normally have difficulty accomplishing. The scaffolding assistance can be phased out as students develop a working cognitive schema, an understanding of the concepts, and self-efficacy in the subject matter (Schunk, 2012).

Social Cognitive Learning Theories

Social cognitive learning theories contend that although external factors are important, learning is influenced more from the social environment (Schunk, 2012). These learning theories are very relevant to both face-to-face and online classes (Chitanana, 2012; Knabe, 2004; Schunk, 2012; Simms & Knowlton, 2008). Rather than focusing on an individual to understand how learning occurs, social learning approaches focus on the impact of information exchanged among various individuals (Rogers, 2003). Rogers (2003) suggested that instructional leaders utilize modeling techniques that allow learners to observe their teacher's behavior and then produce a similar behavior. Additionally, according to social cognitive theories, successful online designs provide environments with consistent collaboration, reflection, and authentic tasks that promote the identified objectives of the course (Chitanana, 2012).

In general, learners use attainable models and other social influences to develop mindsets that grasp their attention, retention, production, and motivational levels. They are eventually able to internalize skills and strategies to attain their goals through self-observations, self-judgment, and self-reaction (Schunk, 2012). Students' levels of self-efficacy improve when instructors take the time to demonstrate that success is attainable by providing sufficient models and practice time (Schunk, 2012). It is also recommended that instructors provide avenues and options for tutoring and mentoring (Schunk, 2012).

Other important concepts linked to social cognitive learning theories are self-efficacy, self-regulation, and learner choice (Bandura, 1977, 2011). Low self-efficacy in mathematics is often a result of past failed performances and can affect the choices students make in effort, persistence, and achievement. For example, a student with low self-efficacy in mathematics may procrastinate in doing homework or simply give-up when faced with challenging problems.

Frustration is fueled by the lack of confidence to complete the task. Pajares and Miller (1995) stated that an individual's behavior is strongly affected by his or her self-knowledge and self-beliefs. Social cognitive learning theories support the notion that a high level of self-efficacy improves motivation, persistence, and achievement in the content area and, in some studies, has been shown to be a stronger predictor of final grades than aptitude tests like the ACT (Benford & Gess-Newson, 2006).

Constructivist Learning Theories

Constructivist learning theories also emphasize the importance of social factors in learning, however, these theories place emphasis on personal meaning and individual construction of understanding, knowledge, and skills (Schunk, 2012). Individuals hold various beliefs about how they learn in and out of the classroom based on personal, social, and cultural factors (Moll, 2001; Schunk, 2012). Rothwell and Kazanas (2008) mentioned that there are three basic types of learners: goal-oriented, activity-oriented, and learning-oriented. "Each category of individual learner provides clues about how to market instruction, since each suggests what learners seek from it" (Rothwell & Kazanas, 2008, p. 319). It is important for educators to understand the expectations and mindsets of their students because the students' mindsets influence their perceptions of their personal abilities to learn the material. For example, students with a fixed mindset, believe that they have little control over their abilities to perform, whereas students with growth mindsets believe that they can improve their abilities through learning (Dweck, 2008; Schunk, 2012). With an understanding of the expectations of their students, educational leaders are better able to select materials and instructional designs that provide various social support and motivational techniques that provide a beneficial learning environment for the students (Rothwell & Kazanas, 2008).

Chapter Summary

Traditional universities were not designed to provide service to students based on their specific needs and desired careers, especially with today's largely diversified student populations (Christensen et al., 2011). The repurposing of universities' educational missions and implemented strategies for student success "represents a seismic shift in how society, broadly speaking, has judged high quality – moving away from a focus on research and knowledge creation and instead moving toward a focus on learning and knowledge proliferation" (Christensen et al., 2011, p. 11). The pertinent literature supported the general framework for this research, which aimed to better understand the relationships between academic performance and influential characteristics of success from learning experiences (i.e., learning environment and class size), general education background (i.e., ACT Math subscore, current college credit hours earned), and demographic background (i.e., gender and age).

CHAPTER III

METHODOLOGY

Introduction

The reform agenda for higher education in Tennessee started with the Complete College Tennessee Act (CCTA) of 2010. As a result, all 4-year public universities within the state were required to stop offering developmental courses, including developmental mathematics courses (Tennessee Higher Education Commission, 2011). Data indicated that the removal of remedial courses from 4-year institutions increases students' chances to graduate within six years (Complete College America, 2012). In contrast, other data revealed that increased achievement was unlikely because incoming freshmen from high school and transfer students from community colleges were not always prepared to successfully complete college-level courses, particularly college-level math courses, at 4-year universities (American College Testing, 2015; Friedl et al., 2012; Jenkins et al., 2009; Maruyama, 2012). The opposing results indicate that factors other than educational background affect student success and retention in university programs and courses. This chapter describes the general methods used for gathering and analyzing the data in this research project.

Description of the Population and Sample

The data used in this study were gathered from one of entry-level, college math course at a public, 4-year, metropolitan university. After the implementation of the CCTA, this math course was redesigned to serve a student population with no minimum math prerequisite. To maintain consistency, the student data were gathered from classes taught by the same instructor during two consecutive academic years (i.e., Fall 2015, Spring 2016, Fall 2016, and Spring 2017 semesters). Additionally, every participant used in this study was enrolled in one face-to-face or one online section of the course during the four semesters. The students in all sections received comparable resources and instructions, they completed the same assessments (e.g., homework, quizzes, tests), their final grades were comparably calculated, and they had an ACT math subscore on their University transcript.

Variables Analysis

The variables of this study, along with their levels and scales of measurement are presented in Table 3.1. The independent variables (i.e., predictor variables) were student characteristics: learning environment, age, gender, academic rank (i.e., earned credit hours), and ACT math subscore. The dependent variable (i.e., response variable) was academic performance (i.e., final grade) in the math course.

Table 3.1 Variable Analysis

	Variable Labels	Levels of the Variable	Level of Measurement
Dependent Variable	Academic Performance	Final Course Grade	Scale
Independent Variables	Learning Environment	0 = Large, Face-to-Face 1 = Medium, Online 2 = Medium, Face-to-Face	Nominal
	Academic Rank (i.e., Credit hours at the start of the term)	Freshman (0-29.9 hours) Sophomore (30-59.9 hours) Junior (60-89.9 hours) Senior (90+ hours)	Scale
	Age at the start of the semester	Number of years	Scale
	Gender	0 = Female 1 = Male	Nominal
	ACT Math Subscore	Score	Scale

Research Design

To minimize the probability of research misconduct and unethical behaviors within the study, a proposal for the research project was submitted to the Institutional Review Board (IRB) at the University, in accordance to Gliner, Morgan, and Leech (2009). Upon approval, I gathered retrospective data for the sample population from two of the University's data platforms: the learning management system, Blackboard (Blackboard Inc., 2017), and the University's student information system, Banner (Ellucian Company L.P., 2017). The confidentiality of students' data was protected by assigning random identification numbers to the raw data and storing the information in a password protected file. The coded data were analyzed using the Statistical Package for the Social Sciences (SPSS) version 25 (IBM Corp., 2012).

The initial data set contained information for all registered students of the specific instructor, during the identified semesters. However, the data set was refined through the elimination of participants' repeat attempts within the two academic years and the elimination of participants with missing data and outlying values. Inferential statistical analyses were used to identify the predictive relationships between the predictor and outcome variables: students' characteristics (i.e., age, gender, earned credit hours, ACT math subscore, and classroom design and size) and students' academic performances (i.e., final grade in the math course), respectively. To answer the research questions, multiple regression analyses were conducted on the data. I assessed the goodness of fit for the overall models using the adjusted *R* square and inspected the individual regression coefficients for predictive weight on the dependent variable using a significance level of 0.05. To determine whether statistically significant differences existed between students' grades in the various course environments, I first conducted a one-way analysis of variance (ANOVA) and then one-way analysis of covariance (ANCOVA) test when controlling for ACT Math subscores. The results from the statistical analyses may provide instructors and other institutional leaders with a better understanding of the relationships and differences between groups of students and their math course grades.

Data Collection

Data were collected from two of the University's database systems. Specifically, the Blackboard system was used to calculate and record students' final course grades during the 2015-2016 and 2016-2017 academic years, providing quantitative, scale data. Additionally, I grouped participants based on their specific sections and course environments. The University's Banner system provided descriptive data of the participants, namely each student's academic classification (i.e., number of credits earned at the start of the term), age at the start of the term, gender, and highest ACT math subscore.

Data Analysis

This study was a relationship-based design; hence, I did not infer causation (Gliner et al., 2009). The data analyses used in this study were purposed to answer the specific research questions and fulfill the general purpose of this research study: To contribute to the general body of research literature through a structured research design that examined the relationships between students' characteristics and their final grades, and to examine the statistical differences between students' grades in various learning environments.

By nature, some variables within education and social science research (e.g., assessing student success with course grades) are difficult to measure or predict, which raises concern for measurement error in the data analyses. The predictive relationships of students' characteristics on their final course grades were assessed using ordinary least squares regression (LSR). The LSR analyses generated predictive models for course grades with respect to students' characteristics (Field, 2009; Triola, 2014; Wagner, 2013). ANOVA and ANCOVA analyses were conducted to assess the statistical significance of differences between subgroups of students with respect to instructional environments.

For this study, I anticipated a small coefficient of determination or small effect size in the statistical analyses because there are numerous factors, beyond the five considered in this study, that influence student success (Maruyama, 2012; McGrayne, 2011; Patten, 2012; Tai et al., 2005). As a result, there was a higher chance of under-fitting the model (i.e., underestimating the relationships among variables) since important predictors were likely not included in this study due to the limitations and delimitations of the research design (Field, 2009; Osborne & Waters, 2002). In other words, the limitations and delimitations of this research project produced a threat to internal validity and an increased chance of a Type II error (Field, 2009; Gliner et al., 2009; Osborne & Waters, 2002).

Research Questions

The research project considered the following questions:

1. Is there a significant, predictive relationship between students' final grades in a math course and their ages, genders, academic ranks (i.e., number of credits earned at the start of the term), ACT math subscores, and classroom environments (i.e., face-to-face and online)?
2. How well does the combination of students' age, gender, academic rank (i.e., earned credit hours), and ACT math subscore predict academic performance in the face-to-face sections of the math course?
3. How well does the combination of students' age, gender, academic rank (i.e., earned credit hours), and ACT math subscore predict academic performance in the online sections of the math course?
4. Is there a statistically significant difference among students' final math grades in different classroom designs (i.e., large face-to-face, medium face-to-face, and medium online classes), while controlling for ACT math subscores?

Research Question 1 addressed the predictive relationship between the primary independent variables and dependent variable, final semester grades, for all students in the sample population. Research Questions 2 and 3 considered the relationships between students' characteristics and their final grades, while separating the sample population into subsets based on the instructional design, face-to-face and online. Thus, three standard multiple regression models were created to assess the predictive relationships between the identified variables.

Research Question 4 was a comparative question that aimed to reduce the effect of extraneous variables on the dependent variable. The research was designed to establish statistical differences among the adjusted means of students' grades, the dependent variable, in three instructional designs, the independent variable, while controlling for ACT math subscore, the covariate. The data were first analyzed with a one-way analysis of variance (ANOVA) and then with a 1-way analysis of covariance (ANCOVA) test, while controlling for the ACT math subscore.

Chapter Summary

The methodology for this study described a plan that reduced the chances of misconduct and unethical behavior through IRB approval and the consideration of limitations and delimitations. Additionally, the design of this study can be adopted or replicated by other researchers. Multiple linear regressions were used to identify significant relationships and/or differences students' course grades, characteristics, and instructional environments. The procedures of this study were consistent with the methodologies of previous studies that examined the predictive relationships and differences between students' performances in online and face-to-face environments (Cavanaugh & Jacquemin, 2015; Driscoll, Jicha, Hunt, Tichavsky, & Thompson, 2012). These results were intended to provide instructional leaders with a better understanding of the population of students registered in the math course.

CHAPTER IV

RESULTS

The purpose of this research study was to identify the predictive relationships between students' characteristics, the predictor variables, and their final course grades, the criterion variable, in an entry-level, college math course being taught online and in face-to-face classrooms. Additionally, the study aimed to identify differences between student success rates in the three learning environments: large face-to-face, medium online, and medium face-to-face classes.

Refining and Transforming the Data Set

The initial data set included information for 652 registered students during the fall and spring semesters of the 2015-2016 and 2016-2017 academic years. Of the 652 initial participants, 64 participants were removed from the sample because they did not have recorded ACT scores on their university transcripts, and an additional 15 data sets were eliminated from the study because they represented the repeat attempts of students within the data set. Another student was removed from the study because the recorded ACT math subscore was a 2, which was an outlier to all other recorded ACT math subscores that started with a minimum score of 12. Using casewise diagnostics in SPSS, I identified an additional six students as possible outliers within the data set, since their standardized residuals were beyond three standard deviations of the mean standard residual. I reviewed the data to verify the outlier status and noted that the grades for the flagged students ranged from 0 to 12.16. The decision was made to eliminate the six students from the data set. To maintain an accurate perspective of the final grades within this course, other students with failing grades were not removed and the minimum and maximum final grades in the sample population included 2.5 and 99.5, respectively.

The data were gathered from the University's Blackboard and Banner systems (Blackboard Inc., 2017; Ellucian Company L.P., 2017) and coded in SPSS. According to Field (2009), a regression model of the sample data has a greater chance of being generalizable to the population if all underlying assumptions for multiple regression analysis are met. Thus, the assumptions for multiple linear regression were verified. First, the criterion variable, the final grade in the math course, was a scale variable (Field, 2009; Leard Statistics, 2015; Wagner, 2013). Second, the predictor variables (i.e., age, ACT math subscore, gender, instructional environment, and credits earned) were all recognized as scale or nominal variables within the regression data. Dummy codes were used within the analysis to indicate the categorical effect of the two nominal variables: instructional environment (i.e., online and face-to-face) and gender (Wagner, 2013). For example, all female students were coded with a 0 and all male students were coded with a 1. Similarly, face-to-face students were coded with a 0 and online students were identified with a 1. Third, independence of residuals (i.e., independence of observations) was assessed by a Durbin-Watson statistic of 2.105.

Fourth, linearity between the criterion variable and the scale independent variables (i.e., age, ACT math subscores, and credits earned) was assessed in two parts – individually and collectively. I checked for linear relationships between the dependent variable and each quantitative independent variable by visually assessing the partial regression plots (Leard Statistics, 2015; Neter, Kutnner, Nachtsheim, & Wasserman, 1996). Three partial regression scatterplots (Figures 4.1, 4.2, and 4.3) display the response variable's residuals against the specific predictor variable's residuals. These plots provided insight into the linear relationships between the specific predictor variables and the response variable. The somewhat horizontal band of points in the partial regression plot of students' grades and ages (Figure 4.1) indicated that students' age at the start of the semester would likely not provide a useful predictive value for students' grades in the course.

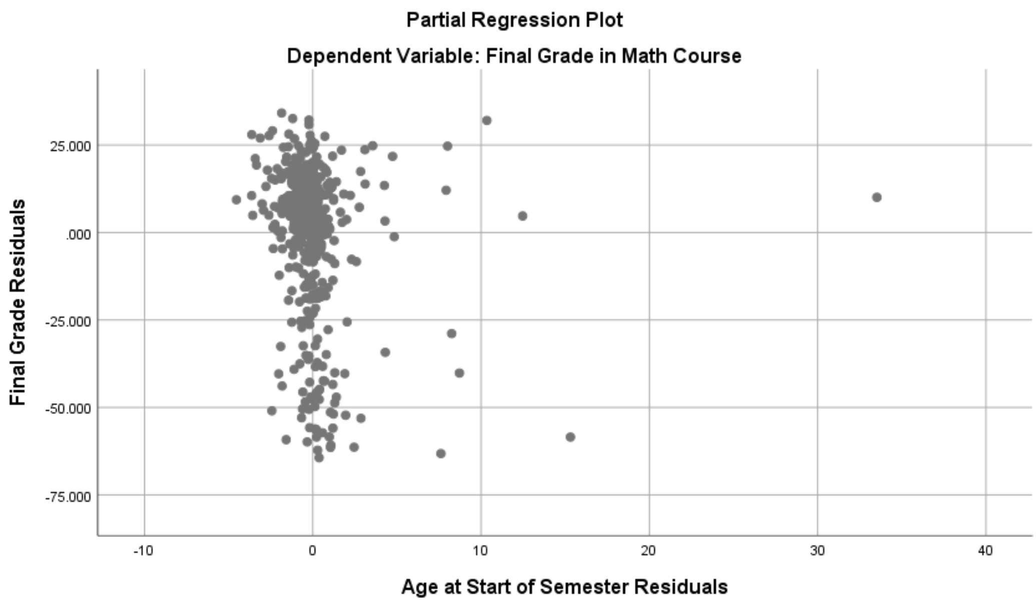

Figure 4.1 Partial regression plot for assessment of linearity between age and final grade

The partial regression plot (Figure 4.2) between students' grades and ACT math subscores displayed a nonzero slope, which indicated that ACT Math subscores could be helpful at predicting students' grades in the regression model.

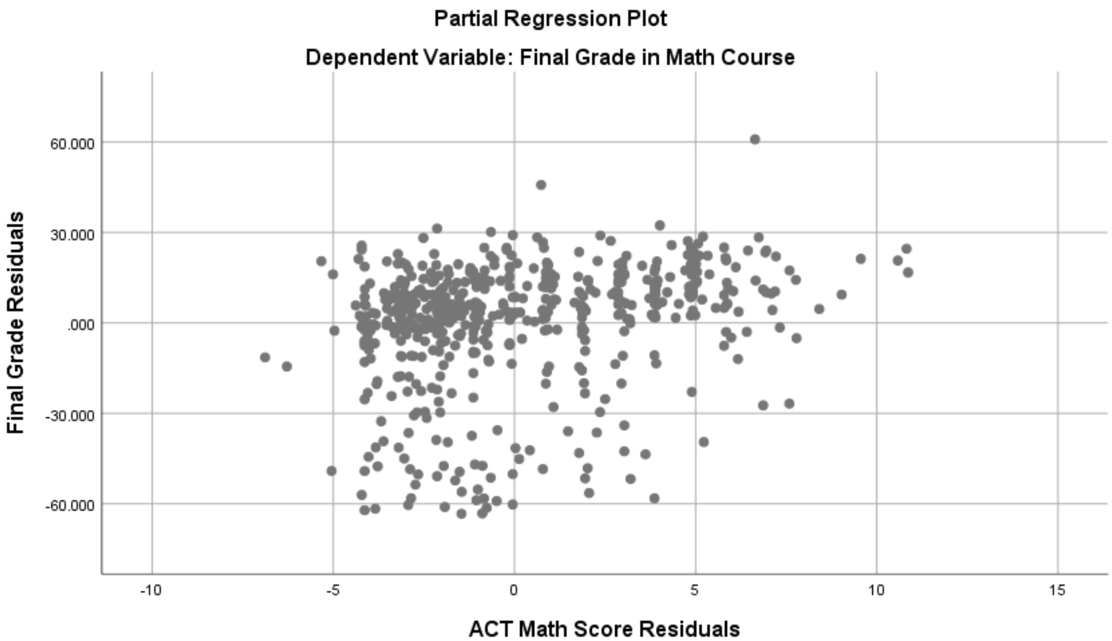

Figure 4.2 Partial regression plot for the assessment of linearity between ACT subscore and final grade

The partial regression plot (Figure 4.3) between students' grades and class rank (i.e., earned credits) displayed a small nonzero slope, which suggested students' earned credits at the start of semester could be helpful predictor of their grades in the model. In general the partial regression plots supported the notion that the model would likely have a small coefficient of determination since there are many extraneous variables affecting students' success and academic performance in the math course.

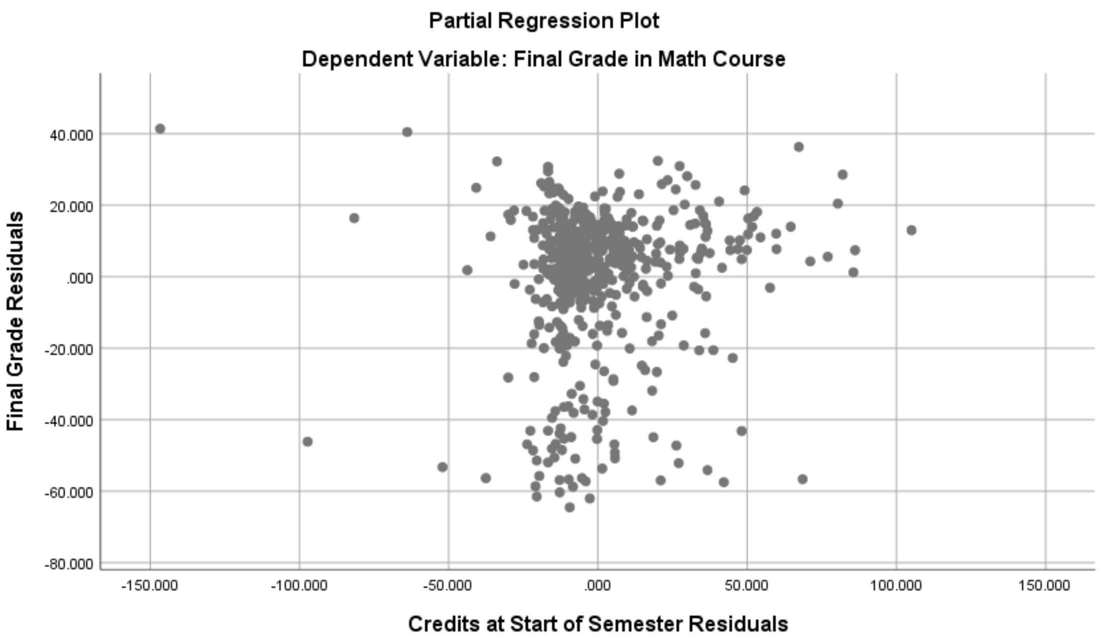

Figure 4.3 Partial regression plot for the assessment of linearity between credits earned and final grade

Linearity between the criterion variable and all predictor variables collectively was assessed using a scatterplot of the studentized residuals against the (unstandardized) predicted values (Figure 4.4). The horizontal band provided evidence that the relationship between students' course grades and the predictor variables is likely linear (Leard Statistics, 2015).

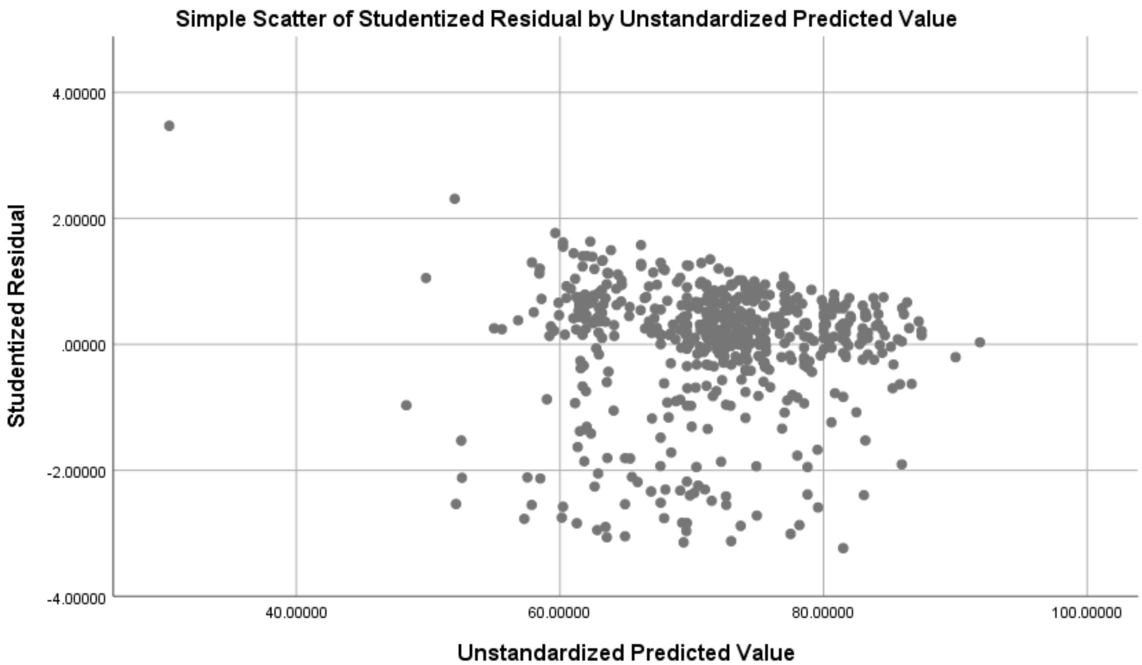

Figure 4.4 Scatterplot of the studentized residuals and predicted values

Fifth, homoscedasticity of the residuals was assessed by visually inspecting the scatterplot of the studentized residuals versus the predicted values (Figure 4.4). The points did not create a funnel shaped graph, but rather a randomly scattered horizontal band (Leard Statistics, 2015); therefore this assumption was accepted. Sixth, multicollinearity was assessed using the tolerance and variation inflation factors (VIF). The tolerance values were all greater than 0.1, which provided evidence that the variables were likely not measuring the same aspect affecting students' grades (Leard Statistics, 2015). This was also verified by considering the bivariate correlations. The largest bivariate correlation, although not larger than 0.700, occurred between students' age and the number of credits earned at the start of the semester (Field, 2009; Leard Statistics, 2015). This was not surprising since nearly 75% of the sample population were first-semester freshmen students.

Lastly, I assessed for normality of the standardized residuals. This was verified using a histogram of the standardized residuals with a superimposed normal curve and with a quantile-

quantile (Q-Q) plot of the studentized residuals (Grande, 2015; Leard Statistics, 2015). Figure 4.5 provides the histogram and Q-Q plots for the regression analysis, which indicated that the standardized residuals were negatively skewed.

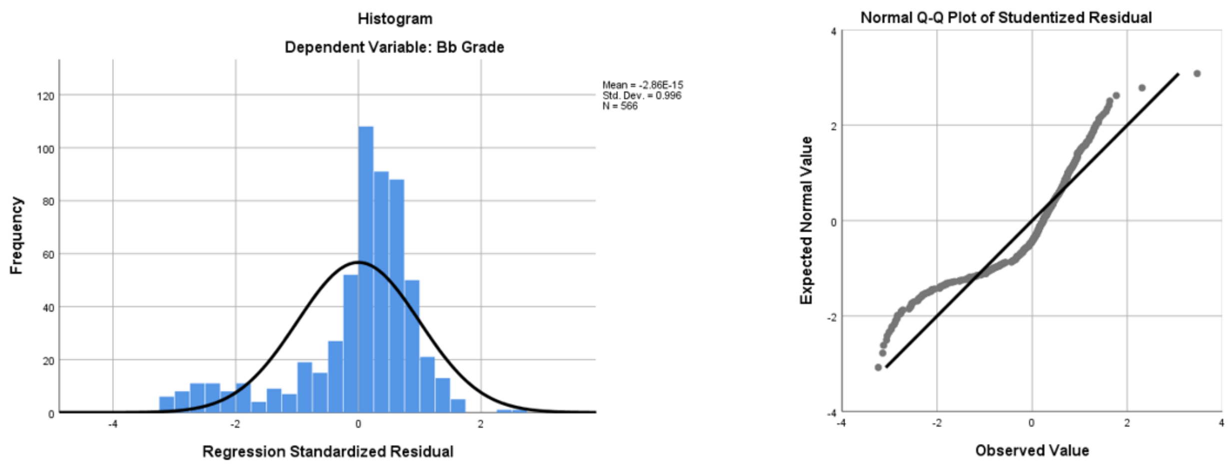

Figure 4.5 Histogram of standardized residuals and Q-Q Plot of studentized residuals using students' final grades in the math course

Since the outlier data were already removed from the sample set, the histogram and Q-Q plot of the residuals helped to identify a negative skew, which resulted in the consideration of a data transformation strategy. I implemented a reverse score, logarithmic transformation (Field, 2009). In other words, the data were reflected to form a right skewed distribution, and then the natural logarithm was applied to eliminate the right tail of the distribution and reduce the positive skew (Field, 2009). The transformed grade values, Y_n', were specifically obtained using the equation: $Y_n' = \ln((\text{Maximum Course Grade} + 1) - Y_n)$, where Y_n was a student's original grade in the course. Figure 4.6 provides evidence of improved normality of residuals in the transformed data.

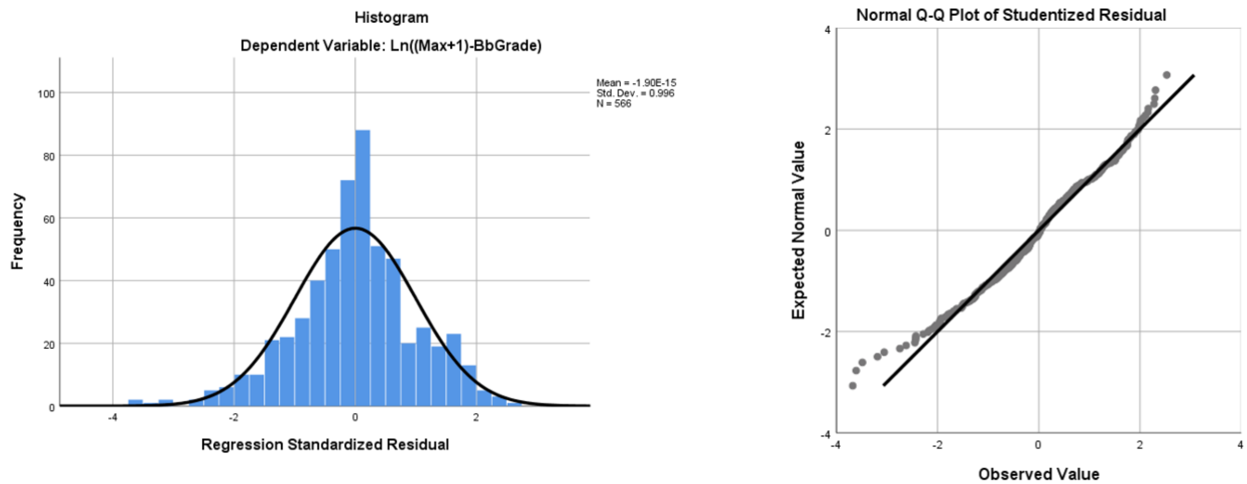

Figure 4.6 Histogram of standardized residuals and Q-Q plot of studentized residuals using the transformed grade data

The statistical analyses used to answer all four research questions were conducted twice, using the final course grades and the transformed grade data.

Participants

The official sample size for this study included 566 participants. An overview of the descriptive statistics for the sample population with unadjusted means, grouped by gender and course design (i.e., large face-to-face, medium online, and medium face-to-face), is provided in Table 4.1. Approximately 14.7% of the participants were enrolled in online sections of the math course and the other 85.3% attended face-to-face sections. The study included one medium sized face-to-face section with 35 students. Since this subgroup was much smaller than the other two instructional designs, students in the medium face-to-face section were grouped into the face-to-face category for Research Questions 1 through 3. It was observed that the minimum grade in the medium face-to-face section was approximately 20 points higher than the minimum grade in the other instructional environments, which produced a smaller range of scores in the medium face-to-face group. Additionally, the standard deviation of students' academic performances in the online sections of the course was larger than the indicated spread within the other designs.

Table 4.1 End of Semester Descriptive Statistics of Sample Population by Instructional Design and Gender

Design (3 cat)	GENDER(1=M,0=F)	*n*	Mean	Grouped Median	Std. Deviation
Face-to-Face, Large Section	FEMALE	290	75.14345	79.45333	18.121083
	MALE	158	66.04937	72.15500	23.964896
	Total	448	71.93616	76.70000	20.807316
Online, Medium Section	FEMALE	61	70.83410	75.20000	22.558440
	MALE	22	62.71000	71.78000	28.157150
	Total	83	68.68072	74.73333	24.257126
Face-to-Face, Medium Section	FEMALE	27	79.87444	80.97667	11.385771
	MALE	8	61.68875	69.25500	21.116419
	Total	35	75.71771	79.01000	15.841925
Total	FEMALE	378	74.78595	79.00500	18.604663
	MALE	188	65.47304	71.83333	24.283674
	Total	566	71.69262	76.61000	21.104671

The gender distribution for this sample indicated that 66.8% were female and 33.2% were male. The mean final grades for male students in all instructional designs were lower than the mean final grades for female students. The ages of students ranged from 16 to 58, and only 3.2% of the sample were categorized as adult or nontraditional learners (Pelletier, 2010). The median ACT math subscore was a 19, while the mode score was a 17. Approximately 70.1% of the students had ACT math subscores below the widely accepted college readiness threshold of 22. Additionally, 72.4% of the students were categorized as freshmen with 0.0-29.9 credit hours at the start of the term, and 43.2% of that freshmen subgroup were new, incoming freshmen with 0 earned credit hours. These proportions were not surprising since the data were gathered from an entry-level math course. However, the percentages limit the generalizability of the study's results.

Findings

Research Question 1

RQ1: Is there a significant predictive relationship between students' final grades in a math course and their ages, genders, academic ranks (i.e., number of credits earned at the start of the term), ACT math subscores, and classroom environments (i.e., face-to-face and online)?

To answer this question, I conducted two ordinary least squares multiple regression analyses using the original data (students' course grades) and the transformed grade data. Since the measure of the proportion of variance (*R* square) is considered to be a positively-biased result, the researched considered the adjusted *R* square when assessing the overall fit of the model (Table 4.2). The regression model using students' course grades explained approximately 11.9% of the variability in students' grades. The low coefficient of determination was not surprising since the model included only five of the many predictive variables of students' success or overall achievement in a course (Tai et al., 2006).

Table 4.2 Summary of Model for Students' Grades in the Math Course

Model	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate	Durbin-Watson
1	.356[a]	.127	.119	19.810722	2.105

a. Predictors: (Constant), Design (Online = 1), Gender (Male = 1), ACT Math Score, Age at Start of Semester, Credits at Start of Semester
Dependent Variable: Course Grade

The *F*-ratio for the analysis of variance (ANOVA) was used to assess how well the regression model predicted the students' grades in the math course when compared to the error within the model (Field, 2009). The results indicated that despite the low *R* square value, the multiple regression model provided a statistically significant prediction of students' final grades in the math course, with *R* square = 12.7%, $F(5,560) = 16.243$, $p < .0005$, and an adjusted *R* Square = 11.9%. Although the predictive model represented a small percentage of the variation in students' grades, it was shown to be a statistically significant model (Table 4.3). This indicated that at least one of the variables was a significant predictor of students' grades.

Table 4.3 ANOVA for Final Grades in the Math Course

Model[a,b]		Sum of Squares	*df*	Mean Square	*F*	Sig.
1	Regression	31874.798	5	6374.960	16.243	.000[b]
	Residual	219780.243	560	392.465		
	Total	251655.040	565			

a. Dependent Variable: Course Grade
b. Predictors: (Constant), Design (Online = 1), Gender (Male = 1), ACT Math Score, Age at Start of Semester, Credits at Start of Semester

The regression model's coefficient table (Table 4.4) indicated that age at the start of the semester, gender (male = 1) and ACT math subscore were statistically significant in predicting students' grades in the math course, $p < .05$. Neither credits earned at the start of the semester or instructional environment (online = 1) showed significant predictive ability on students' final math grades within the regression model of the sample population. The coefficient table indicated that when switching from a female to male student, there was a predicted decrease in the final course grade by approximately 9.403 points. Additionally, for every one year increase in age, the course grade was predicted to decrease by 1.223 points. For every 1-point increase in ACT math score, the course grade was predicted to increase by 1.482 points.

Table 4.4 Coefficients of Predictor Variables for Students' Final Grades in the Math Course

		Unstandardized Coefficients		Standardized Coefficients		
Model[a]		*B*	Std. Error	Beta	*t*	Sig.
1	(Constant)	67.927	9.092		7.471	.000
	Age at Start of Semester	-1.223	.387	-.162	-3.160	.002
	Gender (Male = 1)	-9.403	1.781	-.210	-5.280	.000
	Credits at Start of Semester	.066	.038	.091	1.728	.085
	ACT Math Score	1.482	.251	.238	5.895	.000
	Design (Online = 1)	-1.675	2.651	-.028	-.632	.528

a. Dependent Variable: Course Grade

Based on the characteristics of the sample population and the identified skew of the standardized residuals in the Q-Q plot, I proceeded to conduct a MLR using the transformed grade values. As mentioned, a reverse score, logarithmic transformation was conducted to reduce the negative skew (Field, 2009). Tables 4.5 and 4.6 provide the results of the multiple regression analysis for the transformed data of students' grades. The R square = 15.8%, $F(5,560) = 20.954$, $p < .0005$, and an adjusted R square = 15.0%. The statistical significance of the model indicated that at least one of the regression coefficients was statistically significant.

Table 4.5 Summary of Model for Transformed Grades in the Math Course

Model[b]	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.397[a]	.158	.150	.67841	2.084

a. Predictors: (Constant), Design (F2F = 1), Gender (Female = 1), ACT Math Score, Age at Start of Semester, Credits at Start of Semester
b. Dependent Variable: Transformed Grade Values

Table 4.6 ANOVA for Transformed Grades in the Math Course

Model[a,b]		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	48.220	5	9.644	20.954	.000[b]
	Residual	257.738	560	.460		
	Total	305.958	565			

Dependent Variable: Transformed Grade Values
a. Predictors: (Constant), Design (F2F = 1), Gender (Female = 1), ACT Math Score,
b. Age at Start of Semester, Credits at Start of Semester

Upon examination of the coefficient table for transformed grades (Table 4.7), only gender and ACT math subscores were determined to be statistically significant at predicting students' grades in the course, $p < .05$. This was in contrast to three significant predictors (i.e., gender, ACT math subscores, and age) in the initial data set. This inconsistency was likely due to the skew in data, specifically since over 95% of the students were 23 years or younger.

Table 4.7 Coefficients of Predictor Variables for Transformed Grades in the Math Course

Model[a]		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	*t*	Sig.
1	(Constant)	4.311	.336		12.818	.000
	Age at Start of Semester	.026	.013	.099	1.957	.051
	Gender (Female = 1)	-.306	.061	-.196	-5.024	.000
	Credits at Start of Semester	-.002	.001	-.082	-1.581	.114
	ACT Math Score	-.072	.009	-.330	-8.335	.000
	Design (F2F = 1)	-.042	.091	-.020	-.460	.646

a. Dependent Variable: Transformed Grade Values

A brief comparison of the two regression models suggests that the transformation of students' final grades in the math course was appropriately conducted. According to Field (2009), "a good model should have a large *F*-ratio" (p. 204) because the mean squares (MS_M) will be more than the residual mean squares (MS_R). The larger *F*-ratio in the transformed model provided an indication that this model improved the prediction of students' grades compared to the model's level of inaccuracy (Field, 2009).

Using students' final grades as the criterion variable, the predictive model for a student's final grade, Y_n, where e is the error between the estimated and observed final grade, was written using the following regression equation:

$$Y_n = 67.927 - 1.223(\text{Age}_n) - 9.403\,(\text{Male Gender}_n) + 0.066\,(\text{Credits at start of the term}_n)$$

$$+\, 1.482\,(\text{ACT Math subscore}_n) - 1.675\,(\text{Online Design}_n) + e_n$$

The statistically significant predictors (gender, ACT math subscore, and age) are negatively and positively correlated with students' grades (Table 4.4). From this model, course grades are predicted to decrease by 1.223 points for every 1-year increase in age; the grades of male students' are predicted to be approximately 9.403 points less than females' grades when all other independent variables are held constant; and, course grades are predicted to increase by approximately 1.482 points for every one point increase in ACT Math subscore. Additionally, with all other predictors held constant, the course grades of online students were lower than face-to-face students by approximately 1.675 points.

The second predictive model utilized a reverse score, logarithmic transformation of the dependent variable. Since a reverse-score transformation was conducted, the interpretation of the model's variables required a reversal of the values (Field, 2009). For example, gender was recoded as Female = 1, Male = 0 and instructional design was recoded as Online = 0 and Face-to-Face = 1. Additionally, the concept that "big scores have become small and small scores have become big" (p. 155) was used to interpret the model (Field, 2009). The transformed grade values, Y_n', were obtained using the following equation, where Y_n was a student's final grade in the course:

$$Y_n' = \ln((\text{Maximum Course Grade} + 1) - Y_n)$$

The regression model for the transformed grade data was expressed using the following equation, where e is the error between the estimated and observed transformed values:

$$Y_n' = 4.311 + 0.026\,(\text{Age}_n) - 0.306\,(\text{Female Gender}_n) - 0.002\,(\text{Credits at the start of the term}_n) - 0.072\,(\text{ACT Math subscore}_n) - 0.042\,(\text{Face-to-Face Design}_n) + e_n$$

As mentioned, only gender and ACT math subscores were determined to be statistically significant at predicting students' grades in the course using the transformed data, $p < .05$ (Table 4.7). In addition to reversing the interpretation of the variable, I used the inverse logarithmic function to calculate the expected percentage of change for students' grades with respect to the specific predictor variables (Field, 2009; Institute for Digital Research and Education, 2017).

The general computation for percentage of change for a one-unit increase in a predictor value, while all other independent variables were held constant was determined by the following formula, where the ratio x_1 / x_2 represented the exponentiation of the variable's coefficient:

$$[(x_1 - x_2) / x_2] \cdot 100 = (x_1 / x_2 - 1) \cdot 100$$

For example, the coefficient for gender (female = 1) in the predictive model, Y_n', was -0.306; therefore to determine the percentage of change in students' grades related to gender, I exponentiated the regression coefficient, subtracted 1, and then multiplied by 100 to determine:

$$(\exp(-0.306) - 1) \cdot 100 = -26.36\%$$

Due to the reverse score transformation, it was deduced that when switching from males to females, there would be a 26.36% increase in the course grades.

Similarly, the exponentiated calculation was performed on the ACT math subscore coefficient, -0.072, yielding:

$$(\exp(-0.072) - 1) \cdot 100 = -6.95\%$$

With the reverse score transformation, final course grades were predicted to increase by approximately 6.95% for every one point increase in ACT math subscore. Age, credits earned at the start of the semester, and instructional environment (face-to-face or online) were not significant predictors; however, there was evidence of similar trends to the original model and data. For example, students in the face-to-face environment were predicted to have higher course grades than students in the online section.

Research Question 2

RQ2: How well does the combination of students' age, gender, academic rank (i.e., earned credit hours), and ACT math subscore predict academic performance in the face-to-face sections of the math course? To answer this question, I focused only on students enrolled in the face-to-face course (*n* = 483) and conducted multiple linear regression analyses using both the original course grades and the reverse, log transformed grade data.

The results for both regression analyses were similar to the analyses conducted for RQ1 and are summarized in Tables 4.8 through 4.11. The multiple regression model using students' final grades produced *R* square = 12.3%, $F(4,478) = 16.827$, $p < .0005$, with an adjusted *R* square = *11*.6% . The regression using the reverse, logarithmic transformation yielded a model with *R* square = 14.9%, $F(4,478) = 20.939$, $p < .0005$, and an adjusted *R* square = 14.2%. In both cases the predictive models were statistically significant, with very similar results to RQ1 for this study's sample population.

Table 4.8 Summary of Model for Face-to-Face Students' Grades

Model[b]	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate	Durbin-Watson
1	.351[a]	.123	.116	19.271543	2.203

a. Predictors: (Constant), ACT Math Score, Gender (Male = 1), Credits at Start of Semester, Age at Start of Semester
b. Dependent Variable: Course Grades for F2F Students

Table 4.9 ANOVA for Face-to-Face Students' Grades

Model[a,b]		Sum of Squares	*df*	Mean Square	*F*	Sig.
1	Regression	24997.692	4	6249.423	16.827	.000[b]
	Residual	177525.557	478	371.392		
	Total	202523.249	482			

a. Dependent Variable: Course Grades for F2F Students
b. Predictors: (Constant), ACT Math Score, Gender (Male = 1), Credits at Start of Semester, Age at Start of Semester

Table 4.10 Summary of Model for Face-to-Face Students' Transformed Grades

Model[b]	*R*	*R* Square	Adjusted *R* Square	Std. Error of the Estimate	Durbin-Watson
1	.386[a]	.149	.142	.67369	2.186

a. Predictors: (Constant), ACT Math Score, Gender (Female = 1), Credits at Start of Semester, Age at Start of Semester
b. Dependent Variable: Transformed Grade Values for F2F Students

Table 4.11 ANOVA for Face-to-Face Students' Transformed Grades

Model[a,b]		Sum of Squares	*df*	Mean Square	*F*	Sig.
1	Regression	38.014	4	9.504	20.939	.000[b]
	Residual	216.946	478	.454		
	Total	254.961	482			

a. Dependent Variable: Transformed Grade Values for F2F Students
b. Predictors: (Constant), ACT Math Score, Gender (Female = 1), Credits at Start of Semester, Age at Start of Semester

The coefficient tables (Tables 4.12 and 4.13) provide additional information about the predictive weight and significance of the independent variables on the criterion values. Table 4.12 indicated that age at the start of the semester, gender, and ACT math subscore were statistically significant in predicting students' grades in the math course, $p < .05$. This was consistent with the predictive model from RQ1, which included the sample population (Table 4.4). Specifically, when switching from a female to male student in the face-to-face section, there was an expected decrease in the final course grade by approximately 9.086 points. Additionally, for every one year increase in age for students in the face-to-face class, the course grade was expected to decrease by 1.883 points. For every one point increase in ACT math score for students in the face-to-face sections, the course grade was predicted to increase by

1.373 points. The coefficients of the face-to-face regression model for students' grades were all within one point of the coefficients in RQ1's regression model using students' course grades. This was not surprising since 85.3% of the sample population were face-to-face students.

Table 4.12 Coefficients of Predictor Variables for Face-to-Face Students' Grades in Course

Model[a]		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	*t*	Sig.
1	(Constant)	82.300	15.147		5.434	.000
	Age at Start of Semester	-1.883	.743	-.157	-2.535	.012
	Gender (Male = 1)	-9.086	1.873	-.211	-4.852	.000
	Credits at Start of Semester	.073	.050	.089	1.455	.146
	ACT Math Score	1.373	.266	.226	5.158	.000

a. Dependent Variable: Course Grades of F2F Students

The coefficients in Table 4.13 were interpreted using the same reverse score, exponentiation calculations from RQ1. The transformed data model predicted that when switching from a male to female student, the course grade would increase by approximately 26.94%. This predictive relationship corresponds to the predicted decrease of a male's course grade by 9.086 points (Table 4.10). Additionally, according to Table 4.13 and using the reverse score process, for every one point increase in ACT math subscore, there was an expected 6.67% increase in course grade.

Table 4.13 Coefficients of Predictor Variables for Face-to-Face Students' Transformed Grades

Model[a]		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	*t*	Sig.
1	(Constant)	4.245	.538		7.885	.000
	Age at Start of Semester	.024	.026	.056	.915	.361
	Gender (Female = 1)	-.314	.065	-.205	-4.802	.000
	Credits at Start of Semester	-.002	.002	-.052	-.871	.384
	ACT Math Score	-.069	.009	-.319	-7.381	.000

a. Dependent Variable: Transformed Grade Values for F2F Students

Research Question 3

RQ3: How well does the combination of students' age, gender, academic rank (i.e.,earned credit hours), and ACT math subscore predict academic performance in the online sections of the math course? To answer this question, two multiple linear regression analyses, using both the original course grades and the transformed score data, were conducted using the online students' data (n = 83).

The multiple regression modelS (Table 4.14 and Table 4.15) with students' final grades produced R Square = 14.7%, $F(4,78) = 3.359$, $p < .05$, and an adjusted R square = 10.3% . The regression using the reverse, logarithmic transformed data (Table 4.16 and Table 4.17) yielded a model with R square = 20.4%, $F(4,78) = 4.998$, $p < .005$, and an adjusted R square = 16.3%. Thus, in both cases, the predictive models were statistically significant, $p < .05$.

Table 4.14 Summary of Model for Online Students' Grades

Model[b]	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.383[a]	.147	.103	22.971248	1.914

a. Predictors: (Constant), ACT Math Score, Gender (Male = 1), Credits, Age

b. Dependent Variable: Course Grades for Online Students

Table 4.15 ANOVA for Online Students' Grades

Model[a]		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7090.566	4	1772.641	3.359	.014[b]
	Residual	41158.904	78	527.678		
	Total	48249.470	82			

a. Dependent Variable: Course Grades for Online Students

b. Predictors: (Constant), ACT Math Score, Gender (Male = 1), Credits, Age

Table 4.16 Summary of Model for Online Students' Transformed Grades

Model[b]	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.452[a]	.204	.163	.71767	1.926

a. Predictors: (Constant), ACT Math Score, Gender (Female = 1), Credits, Age

b. Dependent Variable: Transformed Grade Values for Online Students

Table 4.17 ANOVA for Online Students' Transformed Grades

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.297	4	2.574	4.998	.001[b]
	Residual	40.174	78	.515		
	Total	50.471	82			

a. Dependent Variable: Transformed Grade Values for Online Students

b. Predictors: (Constant), ACT Math Score, Gender (Female = 1), Credits, Age

The analysis of the coefficient tables (Tables 4.18 and 4.19) provided additional information about the predictive weight and significance of the independent variables on online students' grades. In both analyses, the only predictive variable with statistical significance at $\alpha = 0.05$ was the ACT math subscore. Table 4.18, the model using students' course grades, predicted a 1.884 grade improvement for every one point increase in ACT math score. Similarly, Table 4.19 indicates that the reverse, log transformed data model predicted that if the ACT math subscore increased by one point, the predicted percentage of change in grade would improve by 8.61%.

Table 4.18 Coefficients of Predictor Variables for Online Students' Grades in Course

Model[a]		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	*t*	Sig.
1	(Constant)	51.446	19.669		2.616	.011
	Age at Start of Semester	-1.042	.533	-.233	-1.955	.054
	GENDER(1=M,0=F)	-8.980	5.768	-.164	-1.557	.124
	Credits at Start of Semester	.125	.083	.178	1.508	.136
	ACT Math Score	1.884	.769	.261	2.448	.017

a. Dependent Variable: Course Grades for Online Students

Table 4.19 Coefficients of Predictor Variables for Online Students' Transformed Grades

Model[a]		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	*t*	Sig.
1	(Constant)	4.676	.608		7.690	.000
	Age at Start of Semester	.026	.017	.180	1.561	.123
	Gender (Female = 1)	-.234	.180	-.132	-1.298	.198
	Credits at Start of Semester	-.003	.003	-.151	-1.325	.189
	ACT Math Score	-.090	.024	-.385	-3.747	.000

a. Dependent Variable: Transformed Grades for Online Students

Research Question 4

RQ4: Is there a statistically significant difference among students' final math grades in different classroom designs (i.e., large face-to-face, medium face-to-face, and medium online classes), while controlling for ACT math subscores and then gender?

Initially, an Analysis of Variance was conducted to determine if there were statistical differences in the mean course grades of the three classroom environments. The dependent variable was students' final grades in the math course and the independent variable was the instructional design. Assumptions of the ANOVA were verified. First, the dependent variable, course grades, was measured on a continuous level. Second, the independent variable consisted of three independent groups – large face-to-face, medium face-to-face, and medium online classes. Third, every participant was registered in one instructional design category, which satisfied the independence of observations assumption. The assumption of normality was not met in any of the independent variable's subgroups; however, the one-way ANOVA is considered to be robust to deviations of normality (Leard Statistics, 2017b); therefore, for the purpose of this study, the one-way ANOVA was conducted using the original data of students' final grades and using the reverse, logarithmic transformed data of students' grades.

The ANOVA procedure continued with the assessment of the assumption of homogeneity of variances for the raw, course data and then the reverse, logarithmic transformed data set. Levene's test of equality of variances for students' course grades (Table 4.20) indicated statistical significance; thus, the assumption of homogeneity of variances was violated (p = .044) for using the raw, course data. However, Levene's test of equality of variances for the transformed data set (Table 4.21) met the assumption of homogeneity of variances (p = .149). As a result, two different one-way ANOVA procedures were conducted for the data sets.

Table 4.20 Levene's Test of Homogeneity of Variances Using Students' Course Grades

		Levene Statistic	*df*1	*df*2	Sig.
Course Grades	Based on Mean	3.143	2	563	.044
	Based on Median	2.032	2	563	.132
	Based on Median and with adjusted df	2.032	2	546.997	.132
	Based on trimmed mean	2.626	2	563	.073

Table 4.21 Levene's Test of Homogeneity of Variances Using Transformed Grades

		Levene Statistic	*df*1	*df*2	Sig.
Transformed Grade Data	Based on Mean	1.912	2	563	.149
	Based on Median	1.790	2	563	.168
	Based on Median and with adjusted df	1.790	2	556.158	.168
	Based on trimmed mean	1.856	2	563	.157

The raw course grades did not meet the assumption of homogeneity of variances; therefore, I utilized a modified version of the ANOVA, the Welch ANOVA (Leard Statistics, 2017b). The result of Welch's ANOVA is displayed in Table 4.22 and indicated that there were no statistically significant differences between the course grades in the large face-to-face, medium online, and medium face-to-face classes; Welch's $F(2,80.016) = 1.728$, $p = .184$. Since the Welch ANOVA was not statistically significant (i.e., $p > .05$), a post hoc test was not conducted.

Table 4.22 Welch ANOVA Test of Equality of Means for Students' Course Grades

	Statistic[a]	*df*1	*df*2	Sig.
Welch	1.728	2	80.016	.184

a. Asymptotically F distributed.

The reversed, logarithmic transformed data met the assumption of homogeneity of variances; therefore, an interpretation of the standard 1-way ANOVA was conducted (Leard Statistics, 2017b). ANOVA results, presented in Table 4.23, showed no statistically significant differences between the group means of the various learning environments, $F(2,563) = .573$, $p = .564$. Since the one-way ANOVA was not statistically significant (i.e., $p > .05$), the investigator did not continue with the Tukey post hoc test. The results of the transformed data corresponded to the results of the original data. The inferential statistics indicated that there were no statistically significant differences; therefore, the null hypothesis $H4_o$ was not rejected and the alternative hypothesis, $H4_a$, was not accepted.

Table 4.23 ANOVA for Transformed Grades

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.621	2	.311	.573	.564
Within Groups	305.337	563	.542		
Total	305.958	565			

I conducted a one-way analysis of covariance (ANCOVA) to determine whether there were statistically significant differences between the mean course grades of students in the medium online class, medium face-to-face class, and large face-to-face class, while controlling for the ACT math subscores. This statistical test was deemed appropriate upon consideration of the following assumptions. First, the dependent variable, students' course grades, was a continuous scale measure. Second, the independent variable consisted of three independent groups – medium online, large face-to-face, and medium face-to-face students. Third, the covariate variable, ACT math subscores, was measured at the continuous level. Fourth, there were different participants in each category (i.e., class design) of the independent variable, which satisfied the independence of observations assumption. Next, the assumption of homogeneity of regression slopes was assessed. According to Field (2009), this means "that the relationship between the outcome (dependent variable) and the covariate is the same in each of [the] treatment groups" (p. 413). A scatter plot, provided in Figure 4.7, was used to visually assess the linear relationships between students' final grades and their ACT math subscores for each instructional design.

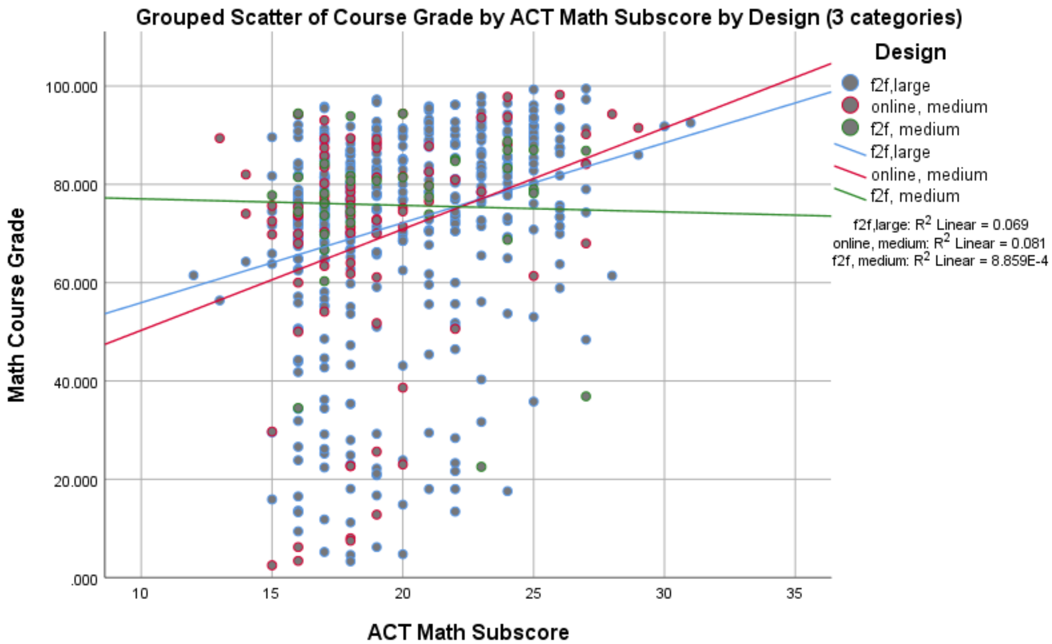

Figure 4.7 Grouped scatter plot of course grades by ACT math score and instructional design

Although the lines were not parallel, the linear relationships between the students in the large face-to-face classes and the medium online classes were very similar. The slope of the line for the other subgroup, students in the medium face-to-face, was clearly different. This difference provided cause for doubt as to whether the assumption of homogeneity of slopes was true; therefore, a customized ANCOVA model that included the interaction between the three course designs (independent variable) and the ACT math subscores (covariate) was determined (Field, 2009; Leard Statistics, 2017a). The results, presented in Table 4.24, indicated that the interaction term between designs and ACT math subscores was not statistically significant, $F(2,560)$ = 1.781, p = .169. Thus, the assumption of homogeneity of regression slopes was accepted.

Table 4.24 Tests of Between-Subjects Effects for Homogeneity of Regression Slopes

Source[b]	Type III Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Corrected Model	18652.492[a]	5	3730.498	8.966	.000	.074
Intercept	15122.524	1	15122.524	36.346	.000	.061
Design (3 types)	1786.217	2	893.109	2.147	.118	.008
ACT Math Subscore	3496.964	1	3496.964	8.405	.004	.015
Design (3 types) * ACT Math subscore	1482.067	2	741.033	1.781	.169	.006
Error	233002.549	560	416.076			
Total	3160799.543	566				
Corrected Total	251655.040	565				

a. R Squared = .074 (Adjusted R Squared = .066)

b. Dependent Variable: Course grade

Additionally, Levene's test of homogeneity of variance was conducted and the statistic was found to be statistically insignificant (p = .055); therefore, the assumption of homogeneity of variances was met. The assumption of homoscedasticity was assessed by visual inspection of a scatterplot represented in Figure 4.8, which displayed the standardized residuals plotted against the predicted values for each of the instructional designs. The points were not funnel or fan shaped and were fairly randomly spread (Leard Statistics, 2017a).

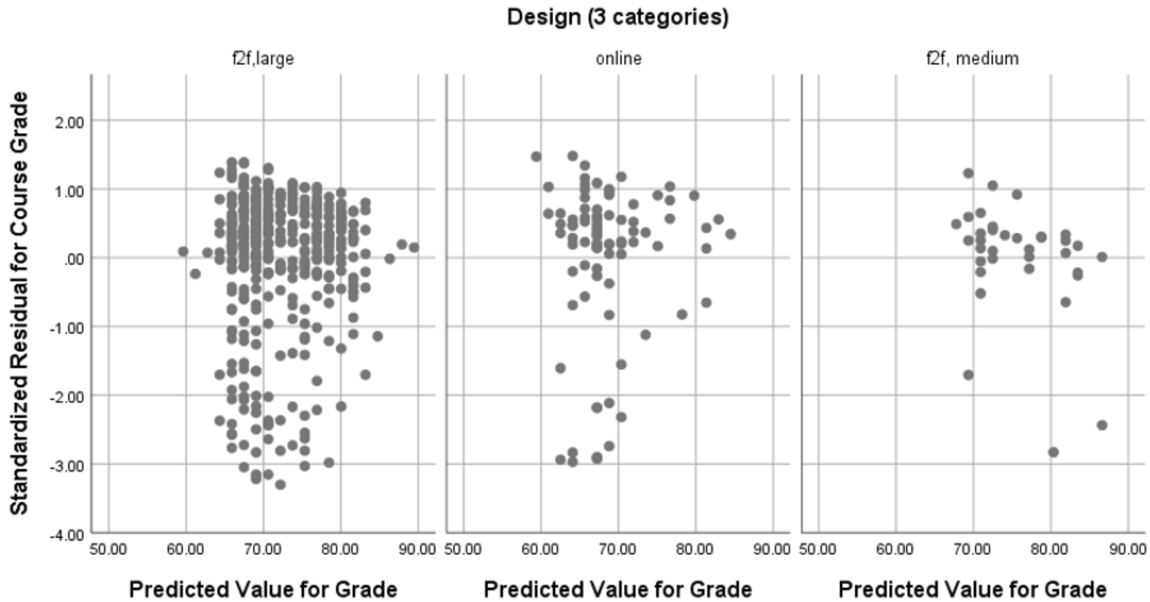

Figure 4.8 Assessment of homoscedasticity of the residuals with a scatterplot of standardized residuals and predicted values of grades in three learning environments

A Shapiro-Wilk test was conducted to assess the normality of the residuals for the dependent variable (course grades), and it was determined that that the residuals were not normally distributed ($p < .05$). A 1-way ANCOVA is fairly robust to deviations of normality (Leard Statistics, 2017a); therefore, for the purpose of this study, the 1-way ANCOVA was still conducted using the course grades.

The adjusted means by the covariate (i.e., ACT math subscores) for groups (i.e., instructional environment) are presented in Table 4.25. From the table, it can be noted that the final course grades were greater in the medium face-to-face group (M = 75.187, SE = 3.454) compared to the large face-to-face group (M = 71.747, SE = .966) and the medium online group (M = 69.923, SE = 2.251), respectively. However, after controlling for the ACT math subscore, the differences among students' course grades between the three instructional designs were not statistically significant, as depicted in Table 4.26. Specifically, $F(2,562) = .820$, $p = .441$. Based on this result, a post hoc test was not conducted.

Table 4.25 Adjusted Means of Course Grades by Instructional Environment With ACT Math Subscore Covariate

			95% Confidence Interval	
Design (3 cat)	Mean	Std. Error	Lower Bound	Upper Bound
F2F, Large	71.747[a]	.966	69.851	73.644
Online, Medium	69.923[a]	2.251	65.501	74.345
F2F, Medium	75.187[a]	3.454	68.403	81.971

a. Covariates appearing in the model are evaluated at the following values: ACT Math Score = 19.72.

b. Dependent Variables: Course Grades

Table 4.26 ANCOVA Tests of Between-Subjects Effects by ACT Math Subscore

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	17170.425[a]	3	5723.475	13.718	.000	.068
Intercept	26418.622	1	26418.622	63.319	.000	.101
ACT Math Subscore	15823.868	1	15823.868	37.926	.000	.063
Design (3 categories)	684.611	2	342.305	.820	.441	.003
Error	234484.615	562	417.232			
Total	3160799.543	566				
Corrected Total	251655.040	565				

a. R Squared = .068 (Adjusted R Squared = .063)

b. Dependent Variable: Course Grades

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE STUDY

Introduction

Enrollment continues to increase at many institutions of higher education, but graduation rates have decreased and even stagnated at some universities (Christensen et al., 2011; Complete College America, 2012; Horn et al., 2002). Therefore, it is important for institutional leaders to take a closer look at the data affiliated with courses and programs with lower-than-desired passing rates so that better, data-informed decisions can be made regarding classroom design, resource allocations, and student support resources. This study was designed to take a closer look at the course grades of an entry level math course that many students complete as one of their graduation requirements. The purpose of the study was to investigate whether there were statistically significant predictive relationships between students' characteristics and their final course grades, and to examine whether statistically significant differences existed among the mean grades in various instructional designs of the same course, taught by the same instructor.

Statement of the Problem

The elimination of developmental courses at 4-year public universities resulted in the redesign of many freshman-level courses, to include mathematics courses. In some cases, the redesigns included the reduction or elimination of prerequisite requirements, which diversified the perquisite skills and backgrounds of students registered in those courses. Instructors are challenged to provide educational designs and resources that support success and learning within their courses. As indicated within the literature review, factors other than educational background affect student success; therefore, it is important and beneficial for educational leaders to gain a better understanding of the possible relationships that exist between other various student characteristics and course grades.

Research Questions

1. Is there a significant, predictive relationship between students' final grades in a math course and their ages, genders, academic ranks (i.e., number of credits earned at the start of the term), ACT math subscores, and classroom environments (i.e., face-to-face and online)?
2. How well does the combination of students' age, gender, academic rank (i.e., earned credit hours), and ACT math subscore predict academic performance in the face-to-face sections of the math course?
3. How well does the combination of students' age, gender, academic rank (i.e., earned credit hours), and ACT math subscore predict academic performance in the online sections of the math course?
4. Is there a statistically significant difference among students' final math grades in different classroom designs (i.e., large face-to-face, medium face-to-face, and medium online classes), while controlling for ACT math subscores?

Summary of the Findings

The data used in this study were gathered over two academic years (four semesters) and included students enrolled in face-to-face and online sections of an entry-level math course, taught by the same instructor, at a metropolitan university. Students who repeated the course within those semesters, who had outlier final grades, or who had no ACT math subscores on their transcript were removed from the data set. The three instructional groups were not equal in size. Specifically, the study included 83 students registered in online sections, 35 face-to-face students in a medium size class, and 448 students from large face-to-face sections.

Assessments of the statistical assumptions for multiple linear regression (MLR), analysis of variance (ANOVA), and analysis of covariance (ANCOVA) were conducted, and it was evident that the distributions of the dependent variable (i.e., students' final grades in the math course) and its standardized residuals were not normally distributed, but rather negatively skewed. Thus, I proceeded with a reverse, logarithmic transformation of the dependent variable's data. The statistical analyses conducted for all research questions included tests using the raw and transformed data of students' grades in the course, which helped with the consistency and validity of the results.

To answer Research Questions 1, 2, and 3, I assessed the predictive relationships between students' characteristics and their final grades in the course using multiple regression analyses. In general, the predictive models from the multiple regression models produced low *R* square values, which were not surprising since this study only considered five predictor variables (i.e., age, gender, credits earned at the start of the term, ACT math subscore, and instructional design). Although the models for raw and transformed data represented small percentages of the variation in students' grades, the regression equations were shown to be statistically significant. Closer examination of the models' coefficients indicated that age, gender, and ACT math subscores were statistically significant predictors of students' course grades; whereas, only gender and ACT math subscores showed statistical significance within the transformed data set. Specifically, female students performed better than the male students regardless of the instructional design and students with higher ACT math subscore were more likely to do better in the course.

More specifically, the analyses for Research Question 2 examined the predictive relationships within the face-to-face student subgroup. Using both the raw and transformed data, the resulting linear regression models were statistically significant, and the statistical significance of the predictor variables corresponded to the results from Research Question 1. That is, age, gender, and ACT math scores were significant predictors within the raw data; whereas, only gender and ACT math scores showed significant predictability using the transformed data set. To answer Research Question 3, I examined the predictive relationships with the online student subgroup. In the online group, the only variable with statistical predictive significance was ACT math subscore.

Research Question 4 asked whether statistically significant differences existed among students' course grades, with respect to the three instructional designs. When assessing the assumptions for the ANOVA, I determined that the raw course grades did not meet the assumption of homogeneity, whereas the reverse logarithmic transformed data met this assumption. Thus, two processes were conducted to complete the ANOVA analysis. For the raw course grades, results for a Welch ANOVA determined that there were no statistically significant differences among the mean grades. For the transformed data, a regular one-way ANOVA was conducted, and the results also indicated that there were no statistically significant differences between the groups' means. Therefore, in both cases, post hoc tests were not conducted.

In summary, based on the statistical assessments of this research study, the following conclusions were made. Reject the null hypothesis, $H1_o$, with respect to the gender and ACT math subscore variables. These independent variables were found to have statistical predictive significance in the regression analyses for Research Question 1. In contrast, the null hypotheses associated with classroom environment, age at the start of the semester, and credits earned at the start of the semester could not be rejected. Additionally, the analyses for Research Question 4 did not identify statistically significant differences between the students' grades when grouped according to the instructional designs; therefore, the null hypothesis associated with this question, $H4_o$, could not be rejected.

Implications for Further Study

The changes in student populations and limited availability of resources and funding have caused many university administrators and classroom instructors to take a closer look at the learning outcomes (i.e., course objectives), instructional processes and designs (i.e., delivery methods), and course outcomes (i.e., students' grades and completion records). This is important on several levels because change is inevitable for the majority of today's universities. Christensen and Eyring (2011) addressed the importance of anticipating and initiating change within the university: "the main questions are when it will occur and what forces will bring it about. It would be unfortunate if internal delay caused change to come through external regulation or pressure from new, nimbler competitors" (p. 19). The changes within higher education have already started. For example, the recent changes in Tennessee legislation eliminated the course offerings of developmental classes at public 4-year universities, which altered the designs and prerequisites of many entry-level math courses, to include the math course used in this research study. It is important to consider how this study can be replicated and improved for future research.

The design and methodology for this study have been commonly used when comparing students' achievements of learning and course outcomes in online and face-to-face courses (Cavanaugh & Jacquemin, 2015). According to Cavanaugh and Jacquemin (2015), most of the studies that compare online and face-to-face classes use course data from "one faculty member in one subject at one particular institution. These studies are extremely important as they indicate local scale levels of variation among students; that said, small scale studies are not able to suggest institutional level conclusions" (p. 2). The stated limitations and delimitations of this study align with this assertion. Specifically, the study was delimited to data from one math course at one university and focused on only five independent variables potentially related to the course outcomes.

The descriptive statistics for the course data (Table 4.1) identified that the grade distributions within the three instructional environments were different; however, inferential statistics from this sample population did not indicate that the differences were statistically significant or generalizable to the course population. Despite these results and contradicting reviews on the effectiveness of class environments and size, there is a need to better understand the factors influencing student success. There is also a growing need to better understand the factors influencing student success in online courses because student enrollment in the online environments is increasing. In 2014, over 2.8 million students took all of their higher education instruction at a distance (i.e., through online learning), and approximately 48% of those students completed their exclusive online learning at a public institution. Furthermore, approximately 2.9 million students were enrolled in both face-to-face and online courses, with approximately 85% of those students being enrolled in public institutions within the United States (I. E. Allen et al., 2016). According to I. E. Allen et al. (2016), the data indicate that:

> Many traditional universities are using online courses to meet demands from residential students, address classroom space shortages, provide for schooling flexibility, and/or provide extra sections. The notion of a "distance" for these students changes from being geographically separated to one of time shifting. (p. 11)

This assertion raises the question of determining whether a better balance of instructional designs and environments can be provided to support students and improve academic performance, particularly those attending public universities. For example, would student performance be significantly better in hybrid courses rather than face-to-face or online courses? And if so, what percentage of online and face-to-face instructions would be optimal?

Specific Recommendations for This Study and Conclusions

The pertinent literature supported the notion that male students often have a higher self-efficacy in math than female students (Skaalvik et al., 2015), and higher self-efficacy is often associated with better course performance (Jozkowskia et al., 2008; Klassen et al., 2008; Skaalvik et al., 2015). However, the data analyses in this study revealed that female students were more likely to earn higher course grades than male students, and this predictive relationship was shown to be statistically significant in the face-to-face sections of the course, but not in the online sections of the course. To gain a better understanding of the underlying influences of these results, it would be beneficial for future studies to incorporate a mixed method research design that utilizes both quantitative and qualitative data gathering techniques while the students are enrolled in the course. The qualitative data could be gathered through online surveys and semistructured interviews, and could address available resources, students' levels of self-efficacy and motivation, and components of self-regulated learning (i.e., cognition and metacognition).

Furthermore, the inclusion of a qualitative component would provide researchers with the opportunity to better understand the nontraditional student population. This study was limited to retrospective data; therefore, I identified nontraditional students simply as adult learners, based on age. It was quickly determined that, this classification was not an ideal criterion for understanding the nontraditional group because most students registered in an entry-level math course are freshmen. Specifically, in this study, only 3.2% of the sample population were adult learners. It may be beneficial for researchers entering this specific field of study to gather specific, qualitative data while students are registered in the course. This would allow researchers to gather data that are not available in University records and databases. The use of both quantitative and qualitative data corresponds to epistemological beliefs that support the ideology that both deductive and inductive reasoning, coupled with the use of data triangulation techniques, can be used to recognize truth and, in this case, a better understanding of influential factors affecting student success in the course (Creswell, 2013; Maruyama, 2012; McGrayne, 2011; Patten, 2012).

REFERENCES

Adelman, C. (2006). *The toolbox revisited: Paths to degree completion from high school through college*. Washington, DC: U.S. Department of Education Retrieved from http://www2.ed.gov/rschstat/research/pubs/toolboxrevisit/toolbox.pdf.

Alexander, F. K. (2000). The changing face of accountability: Monitoring and assessing institutional performance in higher education. *Journal of Higher Education, 71*(4), 411-431. doi:10.2307/2649146

Allen, I. E., Seaman, J., Poulin, R., & Straut, T. T. (2016). *Online report card: Tracking online education in the United States*. Retrieved from Education Advisory Board website: http://onlinelearningsurvey.com/reports/onlinereportcard.pdf

Allen, J., Gregory, A., Mikami, A., Lun, J., Hamre, B., & Pianta, R. (2013). Observations of effective teacher-student interactions in secondary school classrooms: Predicting student achievement with the classroom assessment scoring system-secondary. *School Psychology Review*, *42*(1), 76-97.

American College Testing. (2012). ACT profile report: Graduating class 2012 Tennessee. Retrieved from http://www.act.org/newsroom/data/2012/pdf/profile/Tennessee.pdf

American College Testing. (2014). ACT profile report: Graduating class 2014 Tennessee. Retrieved from http://www.act.org/newsroom/data/2014/pdf/profile/Tennessee.pdf

American College Testing. (2015). The condition of college and career readiness 2015. Retrieved from http://www.act.org/content/dam/act/unsecured/documents/Condition-of-College-and-Career-Readiness-Report-2015-United-States.pdf

American College Testing. (2017a). The condition of college and career readines: ACT profile report - national. Retrieved from https://www.act.org/content/dam/act/unsecured/documents/cccr2017/P_99_999999_N_S_N00_ACT-GCPR_National.pdf

American College Testing. (2017b). The condition of college and career readiness 2017: Tennessee key findings. Retrieved from https://www.act.org/content/dam/act/unsecured/documents/cccr2017/Tennessee-CCCR-2017-Final.pdf

Arnold, I. J. M., & Rowaan, W. (2014). First-year study success in economics and econometrics: The role of gender, motivation, and math skills. *Journal of Economic Education*, *45*(1), 25-35. doi:10.1080/00220485.2014.859957

Ashby, J., Sadera, W. A., & McNary, S. W. (2011). Comparing student success between developmental math courses offered online, blended, and face-to-face. *Journal of Interactive Online Learning, 10*(3), 128-140.

Bahr, P. (2010). Making sense of disparities in mathematics remediation: What is the role of student retention? *Journal of College Student Retention, 12*(1), 25-49.

Bailey, M. A., Rosenthal, J. S., & Yoon, A. H. (2014). Grades and incentives: Assessing competing grade point average measures and postgraduate outcomes. *Studies in Higher Education*, 1-15. doi:10.1080/03075079.2014.982528

Baker, T. L., & Velez, W. (1996). Access to and opportunity in postsecondary education in the United States: A review. *Sociology of Education, 69*(1), 82-101. doi:10.2307/3108457

Bandura, A. (1977). Self-efficacy- Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191-215.

Bandura, A. (2011). Impact of family efficacy beliefs on quality of family functioning and satisfaction with family life. *Applied Psychology: An International Review, 60*(3), 421-448. doi:10.1111/j.1464-0597.2010.00442.x

Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (2001). Self-efficacy beliefs as shapers of children's aspirations and career trajectories. *Society for Research in Child Development, 72*(1), 187-206. doi:0009-3920/2001/7201-0012

Barak, M., Hussein-Farraj, R., & Dori, Y. J. (2016). On-campus or online: Examining self-regulation and cognitive transfer skills in different learning settings. *International Journal of Educational Technology in Higher Education, 13*(1), 35-53.

Barkatsas, A., & Malone, J. (2005). A typology of mathematics teachers' beliefs about teaching and learning mathematics and instructional practices. *Mathematics Education Research Journal, 17*(2), 69-90.

Belfield, C., & Crosta, P. M. (2012). *Predicting success in college: The importance of placement tests and high school transcripts* (CCRC Working Paper No. 42). Retrieved from http://academiccommons.columbia.edu/catalog/ac:146486

Benford, R., & Gess-Newson, J. (2006). Factors affecting student academic success in gateway course at Northern Arizona University. Retrieved from http://www2.nau.edu/~facdev-p/TR/Factors.pdf

Biddle, B. J., & Berliner, D. C. (2015). Small class size and its effects. In J. H. Ballantine & J. Z. Spade (Eds.), *Schools and society: A sociological approach to education* (5th ed., pp. 76-85). Los Angeles, CA: Sage.

Blackboard Inc. (Producer). (2017). Blackboard Learn. Retrieved from http://www.blackboard.com/higher-education/index.aspx

Bromberg, M., & Theokas, C. (2016). Meandering toward graduation: Transcript outcomes of high school graduates. *Education Trust.* Retrieved from https://files.eric.ed.gov/fulltext/ED566663.pdf

Cavanaugh, J., & Jacquemin, S. J. (2015). A large sample comparison of grade based student learning outcomes in online vs. face-to-face courses. *Online Learning*, *19*(2).

Chao, R., & Good, G. E. (2004). Nontraditional students' perspectives on college education: A qualitative study. *Journal of College Counseling, 7*(1), 5-12.

Chew, J., Knutson, K., & Martini, E. A. (2014). *Instituting a proactive risk assessment model: The promise and peril of predictive approaches to student success*. Paper presented at the Assessment in Action Conference at Western Michigan University.

Chitanana, L. (2012). A constructivist approach to the design and delivery of an online professional development course: A case of the iEarn online course. *International Journal of Instruction*, *5*(1), 23-48.

Christensen, C. M., & Eyring, H. J. (2011). *The innovative university: Changing the DNA of higher education from the inside out*. San Francisco, CA: Jossey-Bass.

Christensen, C. M., Horn, M. B., Caldera, L., & Soares, L. (2011). Disrupting college: How disruptive innovation can deliver quality and affordability to postsecondary education. Retrieved from https://cdn.americanprogress.org/wp-content/uploads/issues/2011/02/pdf/disrupting_college.pdf

Complete College America. (2011). Time is the enemy: The surprising truth about why today's college students aren't graduating...and what needs to change. Retrieved from http://www.completecollege.org/docs/Time_Is_the_Enemy_Summary.pdf

Complete College America. (2012). Remediation - Higher education's bridge to nowhere. Retrieved from http://www.completecollege.org/docs/CCA-Remediation-final.pdf

Complete College America. (2013). The game changers: Are states implementing the best reforms to get more college graduates? Retrieved from http://www.completecollege.org/pdfs/CCA%20Nat%20Report%20Oct18-FINAL-singles.pdf

Complete College America. (n.d.). Transform remediation: The co-requisite course model. Retrieved from http://www.completecollege.org/docs/CCA%20Co-Req%20Model%20-%20Transform%20Remediation%20for%20Chicago%20final%281%29.pdf

Council for Adult and Experiential Learning. (2005). *Principles in practice: Assessing adult learning focused institutions*. Retrieved from http://www.eric.ed.gov/contentdelivery/servlet/ERICServlet?accno=ED509960

Cragg, K. M., & Henderson, A. E. (2013). Understanding the range of postsecondary institutions and programs. In P. J. Schloss & K. M. Cragg (Eds.), *Organization and administration in higher education* (pp. 3-26). New York, NY: Routledge.

Creswell, J. W. (2013). *Qualitative inquiry and research design: Choosing among five approaches* (3rd ed.): Sage.

D'Lima, G. M., Winsler, A., & Kitsantas, A. (2014). Ethnic and gender differences in first-year college students' goal orientation, self-efficacy, and extrinsic and intrinsic motivation. *Journal of Educational Research, 107*(5), 341-356.

Driscoll, A., Jicha, K., Hunt, A. N., Tichavsky, L., & Thompson, G. (2012). Can online courses deliver in-class results? A comparison of student performance and satisfaction in an online versus a face-to-face introductory sociology course. *Teaching Sociology, 40*(4), 312-331.

Dweck, C. (2008). *Mindset the new psychology of success: How we can learn to fulfill our potential*. New York, NY: Ballantine Books.

Ellucian Company L.P. (Producer). (2017). Banner by Ellucian. Retrieved from http://www.ellucian.com/student-information-system/

Field, A. (2009). *Discovering statistics: Using SPSS* (3rd ed.). London, England: SAGE Publications Ltd.

Fitzpatrick, J. L., Christie, C., & Mark, M. M. (2009). *Evaluation in action: Interviews with expert evaluators*. Los Angeles, CA: Sage Publications, Inc.

Fjortoft, N., & Smart, J. C. (1994). Enhancing organizational effectiveness: The importance of culture type and mission agreement. *Higher Education, 27*(4), 429-447. doi:10.1007/bf01384903

Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. *American Psychologist, 34*(10), 906-911.

Friedl, J., Pittenger, D., & Sherman, M. (2012). Grading standards and student performance in communicty college and university courses. *College Student Journal, 46*(3), 526-532.

Gikandi, J. W., Morrow, D., & Davis, N. E. (2011). Online formative assessment in higher education: A review of the literature. *Computers & Education, 57*(4), 2333-2351. doi:10.1016/j.compedu.2011.06.004

Gliner, J. A., Morgan, G. A., & Leech, N. L. (2009). *Research methods in applied settings: An integrated approach to design and analysis* (2nd ed.). New York, NY: Routledge.

Grande, T. (2015). Creating and interpreting normal q-q plots in SPSS.

Guerrieri, G. M., Wakim, P. G., Keenan, P. A., Schenkel, L. A., Berlin, K., Gibson, C. J., . . . Schmidt, P. J. (2016). Sex differences in visuospatial abilities persist during induced hypogonadism. *Neuropsychologia*, *81*(1), 219-229.

Hagedorn, L. S., & Kress, A. M. (2008). Using transcripts in analyses: Directions and opportunities. *New Directions for Community Colleges*, *2008*(143), 7-17. doi:10.1002/cc.331

Hall, J. M., & Ponton, M. K. (2005). Mathematics self-efficacy of college freshman. *Journal of Developmental Education*, *28*(3), 26-32.

Halpern, D. F., Straight, C. A., & Stephenson, C. L. (2010). Beliefs about cognitive gender differences: Accurate for direction, underestimated for size. *Sex Roles: A Journal of Research*, *64*(5), 336-347. doi:10.1007/s11199-010-9891-2

Horn, L., Peter, K., Rooney, K., & Malizio, A. (2002). Profile of undergraduates in U.S. postsecondary Intitutions: 1999-2000 Statistical analysis report. Retrieved from http://nces.ed.gov/pubs2002/2002168.pdf

Hubbard, D. W. (2010). *How to measure anything: Find the value of "intangibles" in business* (2nd ed.). Hoboken, NJ: John Wiley & Sons, Inc.

Hussar, W. J., & Bailey, T. M. (2016). Projections of Education Statistics to 2023 (NCES 2015-073). *U.S. Department of Education, National Center for Education Statistics*. Retrieved from https://nces.ed.gov/pubs2015/2015073.pdf

Hyde, J. S. (2014). Gender similarities and differences. *Annual Review of Psychology*, *65*(1), 373-398. doi:10.1146/annurev-psych-010213-115057

IBM Corp. (2012). IBM SPSS Statistics (Version 21.0). Retrieved from http://www.ibm.com/support/knowledgecenter/SSLVMB_21.0.0/com.ibm.spss.statistics.help/syn_glm_overview_overview.htm

Institute for Digital Research and Education. (2017). FAQ how do i interpret a regression model when some variable are log transformed? Retrieved from https://stats.idre.ucla.edu/sas/modules/sas-learning-moduleintroduction-to-the-features-of-sas/

Jenkins, D., Jaggars, S. S., & Rokso, J. (2009). *Promoting gatekeeper course success among community college students needing remediation: Findings and recommendations from a Virginia study*. Retrieved from Teachers Comunity College Research Center: http://ccrc.tc.columbia.edu/media/k2/attachments/strategies-promoting-gatekeeper-success-summary.pdf

Jozkowskia, R., Malhotra, N., Shapero, M., & Sizoo, S. (2008). The effects of anxiety and self-efficacy on finance students. *Journal of Instructional Psychology*, *35*(4), 347-356.

Kirst, M., & Venezia, A. (2001). Bridging the great divide between secondary schools and postsecondary education. *The Phi Delta Kappan, 83*(1), 92-97.

Klassen, R. M., Krawchuk, L. L., & Rajani, S. (2008). Academic procrastination of undergraduates: Low self-efficacy to self-regulate predicts higher levels of procrastination. *Contemporary Educational Psychology, 33*(4), 915-931.

Knabe, A. P. (2004). Constructivist learning perspectives in online public reaction classrooms. http://www.prismjournal.org/fileadmin/Praxis/Files/Journal_Files/Issue2/Knabe.pdf

Kobrin, J. L., Kim, Y., & Sackett, P. R. (2012). Modeling the predictive validity of SAT mathematics items using item characteristics. *Educational and Psychological Measurement, 72*(1), 99-119. doi:10.1177/0013164411404410

Kobrin, J. L., & Patterson, B. F. (2011). Contextual factors associated with the validity of SAT scores and high school GPA for predicting first-year college grades. *Educational Assessment, 16*(4), 207-226. doi:10.1080/10627197.2011.635956

Kowski, L. E. (2013). Does high school performance predict college math placement? *Community College Journal of Research and Practice, 37*(7), 514-527. doi:10.1080/10668926.2012.754730

Krumrei-Mancuso, E. J., Newton, F. B., Kim, E., & Wilcox, D. (2013). Psychosocial factors predicting first-year college student success. *Journal of Colelge Student Development, 54*(3), 247-266.

Kulavic, K., Hultquist, C. N., & McLester, J. R. (2013). A comparison of motivational factors and barriers to physical activity among traditional versus nontraditional college students. *Journal of American College Health, 61*(2), 60-66.

Leard Statistics. (2015). Multiple regression analysis using SPSS Statistics. *Statistical tutorials and software guides.* Retrieved from https://statistics.laerd.com/

Leard Statistics. (2017a). One-way ANCOVA using SPSS Statistics. *Statistical tutorials and software guides.* Retrieved from https://statistics.laerd.com/

Leard Statistics. (2017b). One-way ANOVA using SPSS Statistics. *Statistical tutorials and sofware guides.* Retrieved from https://statistics.laerd.com/

Lee, J. (2013). Can writing attitudes and learning behavior overcome gender difference in writing? Evidence from NAEP. *Written Communication, 30*(2), 164-193. doi:10.1177/0741088313480313

Li, K., Zelenka, R., Buonaguidi, L., Beckman, R., Casillas, A., Crouse, J., . . . Robbins, S. (2013). Readiness, behavior, and foundational mathematics course success. *Journal of Developmental Education, 37*(1), 14-36.

Malm, J. R. (2008). Six community college presidents: Organizational pressures, change processes, and approaches to leadership. *Community College Journal of Research and Practice, 32*(8), 614-628. doi:10.1080/10668920802103813

Marsh, C., Vandehey, M., & Diekhoff, G. (2008). A comparison of an introductory course to SAT/ACT scores in predicting student performance. *Journal of General Education, 57*(4), 244-255.

Maruyama, G. (2012). Assessing college readiness: Should we be satisfied with ACT or other threshold scores? *Educational Researcher, 41*(7), 252-261. doi:10.3102/0013189x12455095

Mayes, R., Chase, P. N., & Walker, V. L. (2008). Supplemental practice and diagnostic assessment in an applied college algebra course. *Journal of College Reading and Learning, 38*(2), 7-30.

McGrayne, S. B. (2011). *The theory that would not die- How Bayes' rule cracked the enigma code, hunted down Russian submarines and emerged triumphant from two centuries of controversy*. New Haven, CT: Yale University Press.

Miles, K. H., & Ferris, K. (2015). Designing schools that work: Organizing resources strategically for student success. Watertown, MA: Education Resource Strategies.

Moll, L. C. (2001). Through the mediation of others: Vygotskian research on teaching. In V. Richardson (Ed.), *Handbook of research on teaching* (4th ed., pp. 111-129). Washington, DC: American Educational Research Association.

Moore, J. L., Dickson-Deane, C., & Galyen, K. (2011). E-Learning, online learning, and distance learning environments: Are they the same? *The Internet and Higher Education, 14*(2), 129-135. doi:10.1016/j.iheduc.2010.10.001

Mumby, D. K. (2013). *Organizational communication: A critical approach*. Los Angeles, CA: Sage Publications, Inc.

Neter, J., Kutnner, M. H., Nachtsheim, C. J., & Wasserman, W. (1996). *Applied Linear Statistical Models* (4th ed.). Boston, MA: McGraw-Hill.

Nisbet, S., & Warren, E. (2000). Primary school teachers' beliefs relating to mathematics teaching and assessing mathematics and factors that influence these beliefs. *Mathematics Teacher Education and Development, 2*(1), 34-47.

Northouse, P. G. (2010). *Leadership: Theory and practice* (5th ed.). Los Angeles, CA: Sage Publications, Inc.

Osborne, J. W., & Waters, E. (2002). Four assumptions of multiple regression that researchers should always test. *Practical Assessment, Research and Evaluation, 8*(2). Retrieved from http://pareonline.net/getvn.asp?n=2&v=8

Pajares, F., & Miller, M. D. (1995). Mathematics self-efficacy and mathematics performances: The need for specificity of assessment. *Journal of Counseling Psychology, 42*(2), 190-198.

Parker, T., Bustillos, L., & Behringer, L. (2010). *Remedial and developmental education policy at a crossroads* (Document No. 9010). Retrieved from Education Commission of the States: http://www.gettingpastgo.org/docs/Literature-Review-GPG.pdf

Patten, M. L. (2012). *Understanding research method: An overview of the essentials* (8th ed.). New York, NY: Routledge.

Pelletier, S. G. (2010). Success for adult students. *Public Purpose*, 2-6.

Prensky, M. (2006). Listen to the natives. *Educational Leadership, 63*(4), 8-13.

Purdue University. (n.d.). Semester credit hours guidelines. Retrieved from https://www.purdue.edu/registrar/documents/forms/Credit_Hr_Guidelines.pdf

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Free Press.

Rothwell, W. J., & Kazanas, H. C. (2008). *Mastering the instructional design process: A systematic approach* (4th ed.). San Francisco, CA: John Wiley & Sons, Inc.

Sackett, P. R., Kuncel, N. R., Arneson, J. J., Cooper, S. R., & Waters, S. D. (2009). Does socioeconomic status explain the relationship between admissions tests and post-secondary academic performance? *Psychological Bulletin, 135*(1), 1-22. doi:10.1037/a0013978

Sawyer, R. (2013). Beyond correlations: Usefulness of high school GPA and test scores in making college admissions decisions. *Applied Measurement in Education, 26*(2), 89-112. doi:10.1080/08957347.2013.765433

Schanzenbach, D. W. (2014). Does class size matter? *National Education Policy Center*. Retrieved from http://nepc.colorado.edu/publication/does-class-size-matter

Schanzenbach, D. W. (2016). Long-term impacts of class size reduction. In P. Blatchford, K. W. Chan, M. Galton, K. C. Lai, & J. C.-K. Lee (Eds.), *Class Size: Eastern and Western Perspectives* (pp. 59-79). New York, NY: Routledge.

Schauer, E., Osho, G., & Lanham, B. (2011). A comprehensive analysis of the efficacy of non-cognitive measures: Predicting academic success in a historically black university in south Texas. *Journal of College Teaching & Learning, 8*(4), 43-51.

Schloss, P. J., & Cragg, K. M. (2013). The nature and role of budget processes. In P. J. Schloss & K. M. Cragg (Eds.), *Organization and administration in higher education* (pp. 3-26). New York, NY: Routledge.

Schunk, D. H. (2012). *Learning Theories: An educational perspective* (6th ed.). Boston, MA: Pearson.

Scott, T. P., Tolson, H., & Huang, T. (2009). Predicting retention of mathematics and science majors. *Journal of College Admissions, 204*(Summer), 20-24.

Simms, J., & Knowlton, D. S. (2008). Ideas in practice: Instructional design and delivery for adult learners. *Journal of Developmental Education*, *32*(1), 20-30.

Simplicio, J. (2012). The university culture. *Education*, *133*(2), 336-339.

Skaalvik, E. M., Federici, R. A., & Klassen, R. M. (2015). Mathematics achievement and self-efficacy: Relations with motivation for mathematics. *International Journal of Educational Research, 72*, 129-136. doi:http://dx.doi.org/10.1016/j.ijer.2015.06.008

Southern Regional Eduation Board. (2007). Improving ACT and SAT scores: Making progress, facing challenges. Retrieved from http://publications.sreb.org/2007/07E02_ACT_and_SAT_Test_Scores.pdf

Sparkman, L. A., Maulding, W. S., & Roberts, J. G. (2012). Non-cognitive predictors of students success in college. *College Student Journal, 46*(3), 642-652.

Swan, K. (2003). Learning effectiveness: What the research tells us. In J. Bourne & J. C. Moore (Eds.), *Elements of Quality Online Education, Practice and Direction* (pp. 13-45). Needham, MA: Sloan Center for Online Education.

Tai, R. H., Sadler, P., & Loehr, J. (2005). Factors influencing success in introductory college chemistry. *Journal of Research in Science Teaching*, *42*(9), 987-1012.

Tai, R. H., Sadler, P. M., & Mintzes, J. J. (2006). Factors influencing college science success. *Journal of College Science Teaching, 36*(1), 56-60.

Tatter, G. (2015). Legislative panel says Tennessee students must continue taking ACT test: Bill highlights tension around testing. Retrieved from http://tn.chalkbeat.org/2015/03/11/house-panel-says-tennessee-students-must-continue-taking-act-test/#.VtI2-ubO_x1

Tennessee Board of Regents. (2016). General education requirements and degree requirements. *Office of General Counsel Policies & Guidelines.* Retrieved from https://policies.tbr.edu/policies/general-education-requirements-and-degree-requirements#General-Education-Requirements

Tennessee Higher Education Commission. (2011). Master Plan progress report. Retrieved from https://www.tn.gov/assets/entities/thec/attachments/LM2011_2011%20Master%20Plan%20Progress%20Report.PDF

The University of Tennessee. (2016). 2016-2017 University general education requirement. Retrieved from http://catalog.utk.edu/preview_program.php?catoid=20&poid=8767

Thorndike, E. L. (1913). *The psychology of learning* (Vol. 2). New York, NY: Teachers College, Columbia University.

Triola, M. F. (2014). *Elementary statistics using Excel* (5th ed.). New York, NY: Pearson.

Tversky, B. (2005). Visuospatial Reasoning. In K. J. Holyoak & R. G. Morrison (Eds.), *The Cambridge handbook of thinking and reasoning* (pp. 209-240). New York, NY: Cambridge University Press.

U.S. Department of Education. (2002). Nontraditional undergraduates. *National Center for Education Statistics*. Retrieved from https://nces.ed.gov/pubs2002/2002012.pdf

U.S. Department of Education. (2015a). Web Table 318.45: Number and percentage distribution of science, technology, engineering, and mathematics (STEM) degrees/certificates conferred by postsecondary institutions, by race/ethnicity, level of degree/certificate, and sex of student: 2008-09 through 2013-14. *National Center for Education Statistics*. Retrieved from https://nces.ed.gov/programs/digest/d15/tables/dt15_318.45.asp

U.S. Department of Education. (2015b). Web tables- Demographic and enrollment characteristics of nontraditional undergraduates: 2011-12. *National Center for Education Statistics*. Retrieved from http://nces.ed.gov/pubs2015/2015025.pdf

U.S. Department of Education. (2016). Fast facts - Back to school statistics. *National Center for Education Statistics*. Retrieved from https://nces.ed.gov/fastfacts/display.asp?id=372

University of Tennessee at Chattanooga. (2016a). College of Arts and Sciences: Statement of Mission. Retrieved from http://www.utc.edu/college-arts-sciences/mission.php

University of Tennessee at Chattanooga. (2016b). Online and distance learning definitions. Retrieved from http://www.utc.edu/learn/online/distance-learning-administration/online-definitions.php

Venezia, A., & Jaeger, L. (2013). Transitions from high school to college. *The Future of Children*, *23*(1), 117-136. doi:10.1353/foc.2013.0004

Voyer, D., & Voyer, S. D. (2014). Gender differences in scholastic achievement: A meta-analysis. *Psychological Bulletin*, *140*(4), 1174-1204. doi:10.1037/a0036620

Wagner, W. E. I. (2013). *Using IBM SPSS Statistics for research methods and social science statistics* (4th ed.). Los Angeles, CA: Sage Publications, Inc.

Wilford, M. (2009). Secondary school course grades and success in college. *College and University*, *85*(1), 22-33.

Wladis, C., Conway, K. M., & Hachey, A. C. (2015). The online STEM classroom—Who succeeds? An exploration of the impact of ethnicity, gender, and non-traditional student characteristics in the community college context. *Community College Review*, *43*(2), 142-164. doi:10.1177/0091552115571729

Woodard, T. (2004). The effects of math anxiety on post-secondary developmental students as related to achievement, gender, and age. *Inquiry*, *9*(1), 1-5.

Xu, D., & Jaggars, S. S. (2014). Performance gaps between online and face-to-face courses: Differences across types of students and academic subject areas. *Journal of Higher Education*, *85*(5), 633-659. doi:10.1353/jhe.2014.0028

Zimmerman, S. D. (2014). The returns to college admission for academically marginal students. *Journal of Labor Economics*, *32*(4), 711-754. doi:10.1086/676661

VITA

Angelique Ramnarine is from St. John, U.S. Virgin Islands. She attended the Julius E. Sprauve School on St. John and graduated from the Ivanna Eudora Kean High School on St. Thomas in 2000. From there, she attended The University of Tennessee at Chattanooga and received her B.S. in Applied and Secondary Mathematics in 2005 and M.Ed. in Secondary Mathematics in 2007. Angelique has taught at the University of Tennessee at Chattanooga for over 12 years and is currently a senior math lecturer. She is the course coordinator for one of the entry-level math courses and has spent several semesters working to improve the online and face-to-face instructional designs. Additionally, Angelique is an instructor with the Upward Bound Math Science TRIO Program, which serves low-income and first-generation college bound high school students.