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Mathematics Learning Support Models and Student Success at a Tennessee Community College

A dissertation

presented to

the faculty of the Department of Education

East Tennessee State University

In partial fulfillment

of the requirements for the degree

Doctor of Education in Educational Leadership

by

Bobby Allen Dixon

August 2016

Dr. W. Hal Knight, Chair

Dr. Donald Good

Dr. Keith Johnson

Dr. James Lampley

Keywords: Remediation, Learning Support, Mathematics, Underprepared

ABSTRACT

Mathematics Learning Support Models and Student Success at a Tennessee Community College

by

Bobby Dixon

Every year thousands of students make preparations to pursue a college degree. Many are high school seniors, but a large percentage of the population are nontraditional age students who are years removed from a formal classroom setting. Included in the list of preparations is an examination whose results will be used to determine each individual's readiness to be academically successful at the collegiate level. These examinations assess student's abilities in the areas of reading, English composition, and mathematics. The results of these examinations show that at the community college level more than half of these students will need remediation in one of these subject areas. Mathematics is most often the area where deficiencies are identified. Therefore, the purpose of this study was to determine if there are significant differences between 4 mathematics learning support models based on student performance in 2 college level mathematics courses at a 2-year community college in Tennessee.

The subjects of this study were students who were enrolled in MATH 1530, Probability and Statistics, or MATH 1630, Finite Mathematics, from the fall 2011 semester through the spring 2016 semester. Students with ACT, SAT, or ACT Compass exam scores meeting or exceeding established benchmark scores were excluded from the study. Each record also included the learning support model each student participated in, the final letter grade for the course, grouped ACT mathematics subscores, age grouping, and enrollment status.

The results of the study indicated significant differences in student success between learning support models for all research questions involving MATH 1530, Probability and Statistics. Comparisons between ACT mathematics subscore groupings, age groupings, and enrollment

status also indicated significant differences in student success. In each case, the current corequisite learning support model proved to be the least successful in preparing students for success in MATH 1530.

Three of the 8 research questions involving MATH 1630, Finite Mathematics, also indicated significant differences in student success between learning support models, with the current corequisite learning support model proving less successful in preparing students for success in MATH 1630.

DEDICATION

This work is dedicated to my family. To my children, Caitlin and Alan, who have accepted my practice of lifelong learning as normal, I am proud of your academic achievements and hope that my efforts have been positive examples for the both of you. To my wife, Beth, who has been instrumental in all my collegiate successes. You have been a source of unfaltering support over the last 29 years, providing the foundation that has held fast through every difficulty I have faced. You have inspired me to be more than I could have been without you. Thank you, and I love you all.

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I would also like to thank the Office of Planning, Research and Assessment at Walters State Community College. Compiling the data for this study yielded tens of thousands of records, which were formatted in the most optimum way that allowed me to separate the data I needed from the data I did not. Their work saved countless hours of data formatting, and their support is also noted.

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CHAPTER 1

INTRODUCTION

Since 2009 college retention and completion has gained nationwide attention. During an address to a Joint Session of Congress in early 2009, President Barack Obama voiced his goal that America would become the country with the highest percentage of college graduates in the world by the year 2020. As a result of the President's address, many state, federal, and private entities have been working diligently to align themselves with this goal (Duncan, 2010). One of the private entities that has proven most influential is Complete College America (CCA). CCA is a national, nonprofit organization that has established the goals of increasing the number of Americans with postsecondary certifications or degrees and closing the attainment gap for ethnic minority populations and those populations of students who can be considered financially underprivileged (Fain, 2012). CCA has identified five points that are considered critical in improving the success rates for today's college students. One of these points is the replacement of prerequisite remediation models with corequisite remediation courses for students whose assessment scores on college admissions examinations indicate they are not prepared for college level work in specific general education subject areas (Game changers, n.d.).

Remediation has been present in colleges for many years and can be defined as the practice of correcting academic deficiencies in specific subject areas for the purpose of preparing students for college level academics (Reforming Remedial Education, n.d.). Many students enter college without the skills that are needed for academic success. Some enter college immediately after high school graduation, and some enter later in life as adult learners. Standardized entrance exams have long been used to determine remediation needs and, because these exams typically have English, reading, and mathematics components, it is usually these disciplines for which

remediation courses are offered. Students whose scores on these exams fall below established benchmarks are deemed in need of remediation.

Traditionally remediation courses have been offered in the form of prerequisite coursework. Prerequisite remediation requires students to take one or more courses that are intended to resolve the academic deficiencies indicated by standardized entrance exam scores before they are allowed to register for college level courses in these academic areas (Bader & Hardin, 2002). There have been countless remediation models used over time. Models may consist of a single course or a regimented sequence of courses. Placement in this sequence is determined by exam scores. Courses within these models may have varying numbers of credit hours. Some institutions may award college credit for remedial coursework. Some may only award institutional credit, while others may award no credit at all.

A new remediation model that is quickly becoming popular is corequisite remediation that involves taking academic support courses in conjunction with paired college level courses in the subject area so that remediation is provided in support of the curriculum being covered in the college level courses as they are being covered (Corequisite Remediation, n.d.). Other corequisite models include the practice of embedding extra support normally provided in stand-alone developmental courses within special offerings of college level coursework. As with prerequisite remediation, the need for corequisite remediation is determined through standardized entrance exam scores.

During the 2014 academic year 1,845,787 high school students took the American College Testing (ACT) exam (ACT Profile - national, 2015). The number of high school students taking the Scholastic Assessment Test (SAT) exam during the same time frame is comparable at 1,672,395 (SAT Total Group, 2015). Another exam that is commonly used in instances where

students have not taken the ACT or SAT is the ACT Compass exam. The ACT Compass exam is an untimed, computerized assessment that is often used in determining the need for placement in remediation courses for adult learners and, in some cases, for students with ACT or SAT scores that fall below established benchmarks used to determine remediation requirements (ACT Compass, n.d.). During the 2014 academic year 1,741,062 prospective college students took the ACT Compass exam, a number comparable to the ACT and SAT exams (ACT Profile - national, 2015).

According to the 2014/2015 Tennessee Higher Education Fact Book (2015), 78.6% of the incoming freshmen in the fall 2014 semester at the Tennessee Board of Regents (TBR) and University of Tennessee institutions reported ACT scores. The only other exams used by these systems are the SAT, ACT Compass, and the Assessment of Skills for Successful Entry and Transfer (ASSET) exams (Tennessee Board of Regents, 2012). The ACT ASSET is a paper and pencil assessment given at higher education institutions to students who do not have recent ACT or SAT scores for the purpose of college placement (ACT ASSET, n.d.). It is considered the equivalent to the ACT Compass exam, which is computerized (ACT Compass, n.d.). Because many institutions prefer the computerized ACT Compass exam and reserve the ACT ASSET for special testing circumstances (Compass and ASSET placement tests, n.d.), it is a given that the majority of college freshmen in Tennessee have used either the ACT, SAT, or ACT Compass assessment as their entrance exam.

Statement of the Problem

With nearly 70% of students entering community colleges requiring remedial coursework (Mangan, 2013b), the lack of college readiness is an apparent barrier to the success of college students. The practice of remediation itself has been pinpointed as a barrier as well. Estimates

place the cost of remediation at more than \$3 billion annually, with fewer than 10% of community college students who require remediation completing their degree requirements within 3 years of starting college (Remediation, 2012). The lack of remediation success has led some states to make radical decisions regarding remediation. In Connecticut 60% of community college students are placed in developmental courses annually, and data shows that only 8% of these students will earn a postsecondary credential within 3 years (Turk, Nellum, & Soares, 2015). This situation led Connecticut legislators to pass legislation that discontinued all non college level remediation courses and instituted a requirement for colleges to embed extra support into college level courses in the form of corequisite remediation. In 2013 Florida legislators, in similar fashion, passed State Bill 1720 that made remediation in their community colleges optional for students (Fain, 2013a). Under this new law only 20% of Florida community college students who opted out of remedial education passed an associated college level course during the spring semester of 2014 compared to a 70.5% pass rate for students who followed the remediation recommendations of their college advisors (Smith, 2015c). According to Fain (2013a) only one in four of students who are placed in remedial coursework will earn a postsecondary degree, diploma, or certificate within 8 years. In Tennessee mathematics has proven to be the area where more students are deemed underprepared based on individual sections of the ACT assessment (ACT Profile - state, 2015). It is for this reason that the area of mathematics was chosen for this study.

Tennessee has also enacted remediation reform in higher education. Since remedial education was introduced in Tennessee's community colleges in the early 1980s (Bader & Hardin, 2002), there have been many different courses and sequences that have been used by the various institutions. These courses and sequences, which will be termed learning support models

for the purpose of this study, had always required students to complete a subject area specific prerequisite remediation regimen before they were allowed to register for college level coursework in the subject area. In the fall of 2015 the learning support model was changed. The current model replaces the prerequisite course regimen with a corequisite model where learning support courses are taken alongside college level courses (Mangan, 2013b). Advocates for corequisite remediation applaud the state's move toward reform, citing the existence of an abundance of evidence that corequisite remediation works. Detractors counter with claims that such evidence is nothing more than claims that have yet to be substantiated (Smith, 2015a). It may be difficult to quantify success or failure at the end of the inaugural year of corequisite remediation in the state, as the fall semester of 2015 is also the first semester of the Tennessee Promise program, where qualifying high school graduates can receive free community college tuition. A number of students who would not have been able to attend college are taking advantage of this opportunity, as some community college campuses had spikes in enrollment in excess of 40% (Mangan, 2013b). With two radical changes such as these, it is going to be difficult to accurately credit success, or a lack thereof, to either program.

With the increased focus on remedial education, coupled with its perceived cause-and-effect relationships with student retention and graduation statistics and the lack of standardization in remediation models used between systems of higher education, a better understanding of how various models may impact student success is needed. Because the area of mathematics has been shown to be the academic discipline where support is most often needed, areas for potential improvement identified in this subject area would impact the largest area of need. Therefore, the purpose of this study is to determine if there are significant differences between four mathematics learning support models based on student performance in two college

level mathematics courses at a 2-year community college in Tennessee. The college level courses studied were MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics.

Research Questions

Per TBR Academic Guideline A-100, Learning Support, students are required to reach or exceed a score of 19 on the mathematics section of the ACT assessment to avoid being placed in mathematics learning support courses. For students taking the SAT exam, their mathematics section scores must reach or exceed 460. For the ACT Compass exam, the mathematics section scores must reach or exceed a score of 38 (Tennessee Board of Regents, 2012). Students whose scores fell below these benchmarks comprised the focus of this study. Since the inception of remedial education, there have been many different models used by institutions in an attempt to remediate students who are underprepared for college level work. These models were the focal point of this study, as were differences in student demographics such as full-time versus part-time students and traditional age versus nontraditional age students. In the state of Tennessee, nontraditional age students, or adult students, are those who are 25 years of age or older (Tennessee Higher Education Adult Student Fact Book, 2014).

This study will compare the results of four separate learning support mathematics models that were in use beginning in the fall semester of 2011 and continuing through the end of the spring semester of 2016. The first of these models is Learning Support Model 1 (LS1). This model is a 3 course regimen with three credit hours per course. The most basic of these courses is DPSM 0700, Basic Mathematics. The content of this course can best be described as that covered in middle school mathematics courses and then reviewed in a high school basic mathematics course (L.B. Dixon, personal communication, March 28, 2016). Students who scored below a 15 on the mathematics section of the ACT exam, below a 350 on the mathematics

section of the SAT exam, or below a 21 on the mathematics section of the ACT Compass exam would be placed into this course. Once successfully completed, the students took the remaining two learning support courses in sequential order. The second course in sequence is DSPM 0800, Elementary Algebra. This course covers content that would be consistent with the basic, introductory content of a high school Algebra I course (L.B. Dixon, personal communication, March 28, 2016). Students who scored 15 or 16 on the mathematics section of the ACT exam, between 350 and 400 on the mathematics section of the SAT exam, or between 21 and 25 on the mathematics section of the ACT Compass exam would be placed into this course. Once successfully completed, the students took the third learning support course. The third course is DPSM 0850, Intermediate Algebra. This course covers content that would be consistent with the more advanced content in a high school Algebra I course (L.B. Dixon, personal communication, March 28, 2016). Students who scored a 17 or an 18 on the mathematics section of the ACT exam, between 400 and 460 on the mathematics section of the SAT exam, or between 26 and 37 on the mathematics section of the ACT Compass exam would be placed into this course. Once successfully completed, the students would be allowed to register for college level mathematics courses. The LS1 Model was used during the 2011-2013 academic years, and the population for the study included 2,376 students who participated in the model.

Learning Support Model 2 (LS2) is a five course regimen with one credit hour per course. LS2 was used during the 2013-2015 academic years and the study population contained 773 students who participated in this model. This model consists of five courses of one credit hour each. Students who scored below a 19 on the mathematics section of the ACT exam, below a 460 on the mathematics section of the SAT exam, or below a 37 on the mathematics section of the ACT Compass exam were required to take these five courses, which were offered in either 3-

weeklong or 5-weeklong sections. These courses replaced the first two remedial courses from the LS1 model, with the third course being converted to a college level course as a prerequisite for pre-calculus courses for students who completed the LS2 regimen.

Learning Support Model 3 (LS3) is a corequisite model with a single three-hour course taught alongside a college level mathematics course. LS3 was initiated in the fall of 2015 and the population for the study contained 797 students. The content for the learning support course in LS3 is a course that combines the content from the five courses that made up LS2 and is delivered in a manner that supports the content of MATH 1630, Finite Mathematics, and MATH 1530, Probability and Statistics.

Learning Support Model 4 (LS4) is a remediation model taught in area high schools to seniors who had made below a 19 on the ACT exam. High school seniors are not given the ACT Compass exam, and there is no current provision for the few students who take the SAT exam to qualify for participation in this model. LS4 is called the Seamless Alignment and Integration of Learning Support (SAILS) program, and the population for the study contained 358 students. It is comprised of five modules that are modeled after the five courses that comprised LS2, and students must pass three of the five modules to obtain high school credit, but must pass all five modules in order to fulfill their mathematics deficiencies and be eligible for registration for college level mathematics courses.

The research questions that will be studied are as follows:

1. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who participated in learning support models LS1, LS2, LS3, or LS4?

2. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who participated in learning support models LS1, LS2, LS3, or LS4?
3. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?
4. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?
5. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?

6. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?
7. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?
8. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?
9. Is there a significant difference in the proportion of traditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4?

10. Is there a significant difference in the proportion of nontraditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, and LS3?
11. Is there a significant difference in the proportion of traditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, and LS4?
12. Is there a significant difference in the proportion of nontraditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, and LS3?
13. Is there a significant difference in the proportion of full-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4?
14. Is there a significant difference in the proportion of part-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4?
15. Is there a significant difference in the proportion of full-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in

learning support models LS1, LS2, LS3, and LS4?

16. Is there a significant difference in the proportion of part-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, and LS4?

Significance of the Study

The lack of academic preparedness of students entering colleges nationwide is evident, with more than half of community college students and nearly 20% of college and university students requiring learning support coursework in at least one of three academic areas (Remediation, 2012). One of the reasons for this drastic difference is most community colleges have open enrollment policies as compared to most 4-year institutions that have competitive admissions requirements and, in some cases, are no longer permitted to offer learning support courses (Remediation, 2012).

Only 62% of students who register for learning support courses at a community college will complete their learning support coursework (Remediation, 2012). When considering the percentage of students who will complete their learning support regimen and then complete an associated college level course, the numbers decline. It has been projected that 22.3% of students requiring remediation will actually complete their learning support coursework and the associated college level coursework within a 2-year period (Smith, 2015c). Additionally, only 9.5% of the students who require learning support are projected to complete their degree program within 3 years of beginning the coursework. When looking at the differences between the ACT English, reading, and mathematics exam sections, more students will require

remediation in mathematics than in either of the other two disciplines, and fewer students will successfully complete their mathematics regimen than either of the other two disciplines (Remediation, 2012).

In the state of Tennessee mathematics remediation coursework has changed dramatically in recent years. As recently as the 2011 academic year mathematics remediation in some community colleges consisted of three courses comprised of three semester hours each. Students who made a score of 17 or 18 on the mathematics section of the ACT (or equivalent scores for alternative exams) were placed in a non college level intermediate algebra course. Those with scores of 15 or 16 required a precursor elementary algebra course. Students with scores below 15 were required to take a course in basic mathematics before taking the two algebra courses.

Part of the issues surrounding remediation is the stigma that some associate with the term (Smith, 2015b). In efforts to place a positive emphasis on remediation, newer models were tagged with titles such as adaptive learning (Fain, 2015) and learning support, which is being used by Tennessee community colleges. During this transition, some Tennessee community colleges have used as many as four distinct learning support models in the last 4-years, with little indication of improvements that these changes have spawned. Current TBR Vice Chancellor for Academic Affairs Tristan Denley developed a corequisite remediation program while he was with Austin Peay State University. This program was noted to have increased student success rates in algebra and statistics courses by roughly 10% above traditional remediation models (Jones, 2014). Denley is but one of many educational leaders who subscribe to CCA's stance that corequisite remediation will be the cure-all for the low retention and completion rates of students who do not meet or exceed the benchmark scores of standardized college admissions exams in all areas, especially mathematics. It is the purpose of this study to analyze four distinctly

different models of mathematics remediation to determine if any of the models yield significantly greater levels of student success in the areas of college level probability and statistics and algebra courses. It is also the purpose of this study to leverage what is learned during the study to develop data based recommendations that can be used to improve the remediation process and improve student success in the area of college mathematics.

Definitions of Terms

To aid in understanding this study, a listing of important terms and their definitions has been provided. The following terms are defined as they have been used in this study.

1. College level – In the state of Tennessee a college level course is considered to be of an academic rigor beyond that of the standards associated with high school curriculum and coursework that is deemed to contain collegiate academic rigor.
2. College ready – College ready is a term that describes students who have no academic deficiencies and are prepared for the rigors of postsecondary education (Overview: State Definitions, 2014).
3. Final course grades – in the context of this study this term refers to the letter grades given to students on completion of courses based on their performance in the course. The scores that are used are the letter grades A through D and F. Student records with assigned grades for withdrawals (W) and incompletes (I) were removed from the study (Seamless Alignment and Integrated Learning Support, n.d.).
4. Learning Support – Learning support is defined as academic assistance a student needs to be considered college ready based on the college readiness benchmark scores established by the ACT (Tennessee Board of Regents, 2012).

5. Nontraditional student – A nontraditional student is most often defined by age, with adults over the age of 24 being the defining characteristic for the population (National Center for Education Statistics, n.d.).
6. Remediation – Remediation refers to courses that are intended to strengthen the skills of students entering higher education, most often in the disciplines of mathematics, reading, and writing (Reforming Remedial Education, n.d.).
7. Seamless Alignment and Integration of Learning Support (SAILS). SAILS is a program that allows high schools in conjunction with area community colleges to offer a five module mathematics course for high school seniors with sub benchmark placement scores. Students who pass all five SAILS modules are considered to have met their learning support requirements.
8. Tennessee Board of Regents (TBR). The Tennessee Board of Regents is one of two governing entities in the Tennessee Higher Education system. TBR governs all state-supported colleges of applied technology, community colleges, and 4-year institutions that are not included in the University of Tennessee system.
9. A traditional student is considered to be a student who is under the age of 25 (National Center for Education Statistics, n.d.).

Limitations of the Study

The subjects of this study are students at a 2-year community college in Tennessee that required learning support (remediation) courses in the area of mathematics. Because it is not possible to study four different learning support models in side-by-side trials, archival data from two of the learning support models are used. The study uses archival data beginning with the fall,

2011 semester and continuing through the summer semester of 2015. Data were collected for the 2015-2016 academic year at the end of the fall and spring semesters.

The use of archival data for the first two groups poses limitations in this study. The data analysis was limited by the inability to obtain precise measurements for students' grades from archival data. The use of end of semester letter grades requires the use of Chi-square tests for data analysis. The use of archival data also limits the studying of various student demographics that could have proven significant had it been possible to run the experiment as a side-by-side analysis. These demographics include socioeconomic factors such as household incomes levels, culture, parents' levels of education, and religious beliefs. These demographics were treated as statistical noise in this study.

There are two critical assumptions involved in this study as well. It is being assumed that the standardized mathematics entrance exam section scores are an effective method of gauging the college readiness of the students in these populations. It is also assumed that the use of data in the form of course letter grades and the subsequent Chi-square analyses on said data produces meaningful results.

This study was impacted by the learning support models themselves and the lack of standardization of these learning support models with other state and national learning support models. Therefore, the likelihood that the results from this study can be applied to learning support models used in other institutions or with other populations is questionable.

Overview of the Study

Chapter 1 of this study contains an introduction whose purpose is to define the scope and relevance of the study. This chapter is comprised of sections that provide a statement of the problem, the research questions being studied, the significance and limitations of the study, and

concludes with a concise overview of the study. Chapter 2 provides a review of literature that is related to the topics that comprise the foundation for the study. The contents of this chapter outline the history of remedial education in higher education followed by a theoretical framework of the influences that are driving the current changes in remediation. The chapter concludes with a review of the various barriers that threaten the potential success of remedial education based on the results of various qualitative and quantitative studies that are being used to justify the need to retool remedial education. Chapter 3 provides a description of the purpose of this study and explains the population of student groups and the data from each student in each group. The methodology related to the extraction of the relevant data from the student record archives is explained, as well as the procedures that were followed during the data analysis process. Chapter 4 provides an analysis of the data for each research question posed, along with other pertinent information gleaned from the findings. Chapter 5 offers conclusions based on the data analysis along with recommendations for possible corrective actions and provides potential topics for future followup studies.

CHAPTER 2

REVIEW OF LITERATURE

For nearly half a century changes to state and federal legislation have provided an ever increasing accessibility to higher education for high school graduates. During this time increases in technology and the increased competition in the modern global economy have steadily driven an increase in the need for citizens with education and training beyond a high school diploma. However, as the need for more citizens with postsecondary degrees and certificates has grown, the preparedness of high school graduates for success in higher education has not kept pace. This increase in the volume of students entering institutions of higher learning unprepared for college level work has led to the need to address the issue through remediation within a college setting. This chapter provides a history of remediation in higher education, the application of standardized entrance exams in determining remediation needs, and the issues that have molded remediation from its beginnings as sequential prerequisite course model into the corequisite model that current reformists are advocating.

Every year, high school seniors begin making plans for life after high school graduation. For the fall semester of 2013, 65.9% of high school graduates continued their education by attending 2-year community colleges or 4-year universities (NCES, 2015). With few exceptions, one of the major milestones each of these students had to achieve was the completion of an examination designed to determine the level of college readiness in the areas of reading, writing, and mathematics. During the 2013-2014 academic year, 57% of high school students took the American College Test (ACT) (Tyson, 2014). Of these test takers 64% met the English exam benchmark, 44% met the benchmark in reading, and 43% met the standard in mathematics. Of the students who did not meet readiness benchmarks prior to entering college, over 70% elect to

begin their postsecondary studies at the community college level (Remediation, 2012), and less than 10% of these students will complete a 2-year degree within 3 years. This information highlights the severity of the lack of college readiness among high school graduates, particularly in the mathematics discipline. Increasing the number of Americans with postsecondary credentialing has been an important state and federal goal since President Obama's State of the Union address on January 24, 2012 (Wood, 2012), and addressing the issues surrounding the effectiveness of remedial education should be at the forefront of the agenda.

For several decades developmental education has been one of the most often discussed topics in higher education. Tennessee's remediation models have been in a constant state of change during that time period (Bader & Hardin, 2002), driven primarily by state and federal legislators in efforts to reduce the costs that many associate with remediation, while at the same time searching for ways to increase student success in terms of retention and program completion. Remediation began a major transformation during the 1980s, with more educators trying to understand the role of developmental education in addressing the needs of underprepared college students (Kulik, Kulik, & Schwab, 1983). Also, during this time frame more students than ever began making the transition from high school to higher education. According to the National Center for Education Statistics (2015) college enrollment increased by over 66% from 10,475,055 students to 17,474,835. To determine the need for developmental education among high school seniors, standardized placement exams like the American College Test (ACT) and the Scholastic Aptitude Test (SAT) were used. In 1989 the ACT exam was changed such that the range of possible scores increased to 1-36 from 1-33 (Lindsay, 2015). In the first year of use the national average score in the area of mathematics was 19.9 (National Center for Education Statistics, 1998). In 2015 the national average score in the area of

mathematics was 20.8 (ACT Profile Report-National, 2015). While this national profile report shows the ACT scores composite scores and individual subject area scores remaining relatively stable, the numbers of incoming freshmen during that 25-year period have risen substantially, yielding an increase in the number of students entering college academically unprepared in many areas, most notably mathematics.

There have been scores of studies performed in efforts to determine best practices in the area of remediation. Kulik and Kulik (1991) reported that improved student performance was achieved when remedial coursework had been designed with detailed attention given to student learning goals. Boylan and Saxon (2002) compiled 30 years of remedial studies to conclude that remedial curriculum must be carefully planned and designed then delivered in a variety of methods with multiple sources of student support to maximize student content mastery. A Community College Research Center study recommended that remediation courses be transformed from prerequisite courses intended to remedy deficiencies in specific areas of study to assigning corequisite courses designed to support college level courses (Jenkins, Jagers, & Roksa, 2009). In comparing the outcomes and recommendations of these studies, it is evident that no individual best practice has been identified. Mangan (2015) cited the practices of two states, one of which has made remedial classes optional, as evidence of the lack of agreement on best practices as state and federal legislators who appear to have lost patience waiting for higher education to find an answer and are enacting policies and laws in attempts to drive remediation reform, much to the consternation of developmental educators. According to the organization Complete College America (CCA) 75% of students requiring remediation will actually earn a 2-year college degree or transfer to a 4-year institution (Fain, 2012). With pressure coming from federal and state levels in the forms of President Barack Obama's stated goal of having the U.S.

become the world's leader in having the largest percentage of college graduates per capita by the year 2020 (Duncan, 2010), and Tennessee Governor Bill Haslam's Drive to 55 initiative, which calls for 55% of Tennessee's adult work force will have a postsecondary degree, certificate, or diploma by 2025 (Fain, 2014), the lack of remediation success and its impact on retention and graduation measurements has become the focal point for higher education nationwide. As of January, 2015, the governors of 33 states had bound their states to the CCA organization's alliance (Field, 2015) which includes a commitment to what the organization calls the five Game Changer strategies that will transform higher education by addressing key areas the organization stresses must be addressed in order to improve college retention and graduation, and one of these areas focuses on remediation (Game changers, n.d.).

The History of Remediation

Remediation is not a new concept in higher education. When Harvard University was founded in 1636, tutors were provided to assist underprepared students in Latin and Greek languages (Phipps, 1998). Remediation can be defined as any course or courses that are offered in a postsecondary environment that are intended to strengthening the skills of students entering higher education, most often in the disciplines of mathematics, reading and writing (Reforming Remedial Education, n.d.). These courses are often not considered to be college level work. Other terms that are used interchangeably with remediation include basic skills training, developmental education, and nontraditional coursework (Parmer & Cutler, 2007). One of the first legislative acts to address the needs of remediation was the Servicemen's Readjustment Act of 1944 (Phipps, 1998). Commonly referred to as the G.I. Bill, the Act also provided funds to build hospitals and provide low-interest mortgages available for veterans, Title II, Chapter IV of the Act made provisions for remediation courses, referring to such as refresher courses (The

Servicemen's Readjustment Act of 1944). This act recognized that returning veterans would need assistance assimilating back into a post war civilization and including the resources for what could be deemed developmental education into the G.I. Bill were essential in providing the education and training needed to veterans in a post-war economy.

One of the first studies in the field of developmental education was conducted at Appalachian State University in Boone, North Carolina. Funded by a grant from the Kellogg Foundation in 1976, a consortium of 2-year and 4-year colleges now known as the National Center for Developmental Education at Appalachian State University was established to develop better methods to remediate academically underprepared students in western North Carolina (Spann, 1996). Also during that year the National Association for Remedial/Developmental Education in Postsecondary Education (NAR/DSPE) was established during a 1984 conference of educators specializing in remedial and developmental education (Boylan & Bonham, 2007). During this conference the name of the organization was changed to the National Association for Developmental Education (NADE). NADE's motto exemplifies the goals and objectives of the organization. The organization's motto is, "Helping underprepared students prepare, prepared students advance, advanced students excel" (National Association for Developmental Education, 2013, p.1).

As remedial education entered the 1980s, educators increased their efforts to understand the need for and impacts of developmental education. In 1983 three professors from the University of Michigan compiled the results of 60 previous studies and performed a meta-analysis of the information harvested from these studies (Kulik et. al, 1983). The results of this analysis yielded evidence that both academic success and student retention increased for students who participated in effective developmental courses.

The early 1980s saw the creation of bachelors, masters, and educational specialist degrees in the field of developmental education at colleges such as Appalachian State University and Grambling State University in Louisiana, with Grambling State University establishing the first doctoral program in developmental education in 1986 (Boylan & Bonham, 2007). As of 2011 the Ed.D. program at Grambling State was still the only doctoral degree in the subject area (Jaschik, 2011). However, in 2011 the Texas Higher Education Coordinating Board approved three programs in the discipline. The Board approved Ed.D. programs at Sam Houston State University and Texas State University, along with a Ph.D. degree program also at Texas State University (Jaschik, 2011).

Through the 1990s, as developmental education continued to grow, many states and regions created local and regional developmental education organizations. In 1996 the American Council of Developmental Education Associations (ACDEA) was founded for the purpose of consolidating these multiple organizations in an effort to encourage collaboration and to foster a sense of teamwork among the organizations (Boylan & Bonham, 2007). It was during the latter part of the 1990s that the developmental education movement began to conflict with the agendas of state legislators. Zumeta (1998) commented that even in the presence of a vigorous economy higher education had begun to experience declines in public financial support, and this trend was projected to continue into the 21st century. It was also during this time that legislators from various states initiated efforts to discontinue funding for developmental education at 4-year institutions, citing that the number of students who were properly prepared for college level work were of sufficient number to allow these institutions to fill first year classes without the need to admit underprepared students (Damashek, 1999a).

As developmental education entered the 21st century some aspects of remediation continued to advance. However, critics of developmental education began to voice their opinions regarding the need for reform in the discipline. Beginning in 1996 the Georgia Board of Regents began a progressive overhaul of the state's remediation program in response to the struggles of disadvantaged students in achieving academic success at the postsecondary level (Hebel, 1999), culminating in the restriction of remediation to the community college level exclusively. In an article published in *Black Issues in Higher Education*, Roach (2000) discussed the need to reform what was then a California policy requiring all students to complete remediation coursework within their first year of study to maintain college eligibility. In 2003 Austin of the Lumina Foundation led a project team in the creation of a program called Achieving the Dream (Miller, 2007). Seeing the community college systems as the means to bridge the gap from high school to the 4-year colleges and universities for academically disadvantaged students, Achieving the Dream was launched with the plan to provide the support needed by community colleges to prepare these students for the rigors of college academics. Although the term remediation was not specifically mentioned at the onset of Achieving the Dream, the circumstances that led to the organization's inception indicate the need for reform. In 2010 remediation reform became political with the creation of CCA (Fain, 2012). Supported financially by both the Lumina Foundation and the Bill and Melinda Gates Foundation (Parry, Field, Supiano, 2013), CCA has aggressively lobbied for reform in several areas of higher education, most notably the area of remedial education (Game Changers, n.d.). It is because of these efforts that the design of remedial education has begun to transform.

The current state of remedial education has traditional prerequisite coursework being pushed aside in favor of corequisite remediation. Corequisite remediation calls for the

discontinuing of all courses that must be taken as prerequisites in order to qualify for college level courses in the subject area (Transform Remediation, n.d.). Corequisite remediation requires these courses be replaced with targeted support for the topics covered in a college level course. This support can be offered in the form of a course, or it can be designed as a lab where students receive extra support through computer based exercises, tutoring, and other resources that provide extra help with the topics covered in the college level course. The reason remediation is under fire is simple; legislators and other leaders see remediation as a barrier to college completion. Legislators question the effectiveness of current remediation models, seeing no real progress in retention and completion measurements over the last several years (Smith, 2015a). This has led many to conclude that remediation must be reformed in order to reduce the numbers of students who drop out of college and increase the number of students graduating within reasonable time frames (Remediation, 2012).

As the number of states and institutions that have adopted corequisite remediation models has grown, detractors of corequisite remediation are identifying problems stemming from the mindset advocated by those in the CCA organization. Some have indicated that the lack of remediation options does not serve a racial diverse student population well (Shapiro, 2015). Other states have not only adopted a corequisite remediation model, they gone as far as allowing students to opt out of remedial coursework when standardized test results indicated that deficiencies existed. Results like those from Florida's new remediation model appear to support claims from developmental education professionals that the potential success of corequisite remediation was based on misinterpretations and misapplications of data (Goudas & Boylan, 2012). However, in early 2016 CCA released a report that indicated that over 60% of students in three states passed their gateway math courses taken alongside remediation courses (Smith,

2016). CCA also reported that only 22% of students needing remediation in previous models would have passed these gateway courses within two years of registration. Based on the conflicting information being posted from both sides of the disagreement, the state of remedial education remains in a state of instability.

The Role of Standardized Placement Exams in Remedial Education

Most 4-year colleges require students to submit either SAT or ACT scores (Which Admission Tests, n.d.). Many students take both ACT and SAT exams for the purpose of creating more impressive portfolios when applying to institutions or programs with competitive admissions standards (Lewin, 2013). During the 2014/2015 academic year 1,924,436 students took the ACT exam (ACT Profile Report National, 2015). In comparison, the most recent SAT Profile Report indicated 1,672,395 students took the exam (SAT Total Group Profile Report, 2015). Various states use other examinations, especially at the community college level. For instance, the state of Tennessee uses the ACT, SAT, ACT Compass, and in some instances, the ASSET exam (Augerblick, 2012). The ACT Compass exam is a computer-based examination that, unlike the ACT exam, is untimed (ACT Compass, n.d.). It is often used by adult learners returning to college and by traditional students who take the exam in efforts to avoid remedial coursework. The ACT ASSET exam, like the ACT Compass, is an exam that can be given by higher education institutions in place of a scheduled ACT or SAT exam (ACT ASSET, n.d.). Also like the ACT Compass exam, the grades from the ACT ASSET exam are available immediately after the exam. However, as the ACT Compass is a computerized assessment, the ACT ASSET is a paper and pencil assessment.

The average score on the mathematics section of the exam was 20.96 for the combined years 2011 through 2015. In comparison, the average score for the same time frame for

Tennessee students was 19.14, which was barely over the state's cutoff score that determines placement in remedial mathematics (ACT profile report – state: Graduating Class 2015 Tennessee, 2015). In contrast, the average SAT mathematics score for Tennessee students in 2014 was 570, which was significantly higher than the state cutoff score of 460 (SAT state profile report Tennessee, 2015). Part of the reason for this difference is the requirement of all Tennessee high school students to take the ACT exam during their junior or senior years of high school (Tennessee students hit five-year high on ACT, 2015). Another reason is that while many Tennessee colleges accept either ACT or SAT scores, many of them are de-emphasizing the SAT exam (Safier, 2015) in favor of ACT exam scores.

The ACT organization advocates a benchmark score of 22 in mathematics as evidence that a student has a 50% chance of earning a letter grade of B or higher in a college level mathematics course (Smith, 2015c). In comparison to the ACT's benchmark score of 22, only 30% of Tennessee students met or exceeded the benchmark, compared to 42% nationally (ACT profile report – state: Graduating Class 2015 Tennessee, 2015). The SAT does not publish benchmarks for the individual subject areas of reading writing, and mathematics, only an overall composite of 1,550 (The SAT college and career readiness benchmark, n.d.). Because the scores for the three subject areas are fairly equally weighted and are added to yield the composite score (SAT Total Group Profile Report, 2015), a good faith estimate for a mathematics score equivalent would be to divide the 1,550 composite score by three, which yields roughly a score of roughly 517. This assumption is validated by an ACT document that indicates a total SAT score of 1,030 for the areas of reading and mathematics is equivalent to an ACT composite score of 22, and half of the 1,030 score is 515 (Compare ACT & SAT Scores, n.d.).

The Tennessee Board of Regents (TBR) has established minimum cutoff scores in the subject areas of English, reading and mathematics for each of the standardized exams that state institutions use to determine student placement in developmental coursework (Tennessee Board of Regents, 2012). Scores of 19 on the ACT exam, 38 on the ACT Compass exam, 39 on the ASSET exam, and 460 on the SAT exam are the established cutoff scores in the mathematics subject area. These cutoff scores have changed little since the formalization of developmental education in Tennessee. Formal developmental education was mandated for Tennessee state institutions in 1984 by a mandate that was framed under Guideline A-100. This mandate included provisions for mandatory assessment and placement procedures for students whose ACT composite scores were below 18 (Bader & Hardin, 2002). The assessment chosen for the follow-up evaluations was the Academic Assessment and Placement Program, or AAPP. This procedure remained in effect until 1990.

Following the changes made by ACT to their scoring system in 1989, TBR updated Guideline A-100 in 1990. These changes included increasing the ACT composite score cutoff to 19 and introducing the English and mathematics sub scores. Guideline A-100 was changed five additional times between 1990 and 2001, but few changes to the guideline were substantive (Bader & Hardin, 2002).

The latest change Tennessee has made changes to policies and procedures governing how standardized test scores are used to determine the remediation needs of students was in 2012, when the English cutoff score was reduced from 19 to 18 (Tennessee Board of Regents, 2012). However, these small changes have not yielded the progress desired by many legislators (Smith, 2015a) and calls for drastic remediation reform have been made in the form of criticisms related to the use of standardized exams such as the ACT and the SAT. Many have questioned the

relevance of the benchmark scores in relationship to predicting the college readiness of incoming college freshmen. A college professor who took the SAT as an exercise in evaluating its effectiveness stated that the exams “emphasized speed and stamina over knowledge, and they failed to provide an adequate measure of what a student might actually understand” (Harper & Vanderbei, 2009, p.30). In 2004 researchers compiled the results of a study that indicated that nonacademic factors such as study skills, academic self-confidence, and the psychological benefit of having academic goals and objectives played a bigger role in predicting student success in college than ACT assessment scores (Robbins, Lauver, Le, Davis, Langley, & Calstrom, 2004). Because of the perceived ineffectiveness of standardized exam scores, some colleges are using high school grade point averages (HSGPA’s) alongside or by themselves as predictors of college success and for determining remediation needs (Fain, 2015b). However, some postsecondary educators are concerned about grade inflation practices in the secondary ranks (Lederman, 2009). While average HSGPA’s increased from 2.80 to 3.04 between 1991 and 2003, and nearly twice as many students in 2006 indicated they had earned an A or an A-minus than students in 1992, the average ACT and SAT scores remain relatively unchanged (Goodwin, 2011). Such evidence of the commonality of grade inflation has many among the ranks of college faculty concerned about the possibility of using a student’s HSGPA for the purpose of developmental education placement (Mintz, 2016).

In 2004 an ACT Policy Report was published that provided evidence that nonacademic factors such as study skills, time management skills, note-taking abilities were better indicators of potential student success in higher education than HSGPA and standardized exam scores (Lotkowski, Robbins, & Noeth, 2004). The University of New Mexico has adopted an assessment called SuccessNavigator (Fain, 2015b). The purpose of this nonacademic assessment

is to identify students who may lack sufficient drive to be successful, to identify those who may not readily ask for help, or to identify any other nonacademic barriers that may hinder success. Student advising, counseling sessions, and developmental course needs are assigned based on this assessment (Fain, 2015b). While it is too early to identify results, such assessments may identify issues related to student success that current practices are failing to identify.

Issues Surrounding Remediation

As developmental education has changed throughout the years, the one key ingredient that has remained consistent are the key measurements that are often used to describe its success. According to the CCA publication entitled Remediation: Higher Education's Bridge to Nowhere (2012), a significant number of students needing remediation will never pass their remedial courses nor their college level gateway courses, and the low graduation rates of students who are placed in remedial coursework are issues that the organization's members have been using as leverage to drive remediation reform. The publication also indicates more than 50% of students entering community colleges and nearly 20% of students entering 4-year institutions will require at least one remedial course. Of these, only 40% will successfully complete their remedial course regimen. Of those who successfully complete their remedial coursework, only one in four will successfully complete the colleges level courses for which remediation was required. Finally, only one student in 10 who requires remediation will graduate with a college degree. It is these issues that are driving the calls for remediation reform.

In 2014, 58.8% of first-year students entering Tennessee colleges were placed into remedial courses (Tennessee Higher Education Fact Book 2015). In 1985, 47% of Tennessee's incoming freshman class needed at least one course in what was then called the remedial and developmental program (Bader & Hardin, 2002). Also in 2014 there were 29,362 first-year

students entering TBR institutions (Tennessee Higher Education Fact Book 2015) compared to only 17,557 in the fall of 1985 (Bader & Hardin, 2002). There are more Tennesseans entering college and, judging by the increase in remediation needs, more are entering college underprepared for higher education academics.

With the current state and federal emphasis on retention and graduation, the success of remedial education has never been scrutinized more. One of the most influential organizations that supports remediation reform is CCA (Fain, 2013a). CCA has been able to influence a number of state and federal legislators to support their remediation reform ideas with data that shed a poor light on the success of historic remediation models. Some of this data is found on the organization's website, which indicates 51.7% of students entering 2-year colleges need remediation, with 22% of these students completing their remediation regimens and associated college level courses in 2-years, and 9.5% of these students completing their degree requirements within 3 years (Corequisite Remediation, n.d.). Such deplorable statistics have encouraged states like Tennessee to completely overhaul its remediation models.

However, there are those who have long been involved in remedial education that disagree with CCA's approach to remediation reform and with the organization's push to hastily and completely retool remediation models. Hunter Boylan, director of the National Center for Developmental Education at Appalachian State University, is one who has been involved in remedial education for many years. According to Boylan he has never seen so many drastic changes implemented in higher education based on what he sees as insufficient supporting evidence (Smith, 2015a). However, CCA has convinced the legislators of 33 states and the District of Columbia to join their alliance. To join this alliance state legislators must agree to set goals related to increasing the completion rates for college students, to collect and report

common data metrics, and to develop action plans related to key policy levers (Complete College America, n.d.). One of the policy levels is the establishment of corequisite remediation. Considering the fact that the organization is heavily funded by the Bill and Melinda Gates Foundation, it should be no surprise that CCA has been able to convince so many entities to participate in its program (Fain, 2013a).

Remediation reform has been a constant for decades, but evidence cited throughout the 1980s and 1990s indicate the changes were incremental in nature (Bader & Hardin, 2002). A 1982 study linked the use of computerized tutoring to improvements in high school student remediation (Stacy, 1982). Stacy's study came at a time when the term microcomputer was used to describe what is currently considered a desktop computer and computers and educational software were not a mainstay in the classroom as they are now. It was Stacy's intent to introduce the use of this emerging technology in all educational settings, not just in specialty settings such as working with hearing impaired students. Another study during this time period involved the grouping of students based on abilities and studying the impact these groupings had on student learning (Peterson, 1989). It was found that students in the advanced curriculum tended to learn more than the students who were placed in the courses designed for remediation. It was not determined if the curriculum at the remedial level was the key factor or if the remedial label placed on the students influenced the outcome of the study.

As remediation evolved in higher education in the 1980s, the issue was less about the content in the curriculum and more about the cost associated with the extra courses needed to remediate the growing number of students entering college, with many being underprepared for collegiate academics. Reilly and Cashen (1988) documented the issues surrounding the rising cost of remediation. Their work highlights the efforts of several states to contain the rising costs

associated with remedial coursework, and documents the changes many states were instituting by assuming the administrative responsibilities for remedial education at the state level, transferring these responsibilities from individual institutions and creating an administrative structure that is still in use today.

In the 1990s research in the field of remedial education began to include developmental education as well. Boylan (1995) differentiated between remedial education and developmental education in that while remedial education was designed to counteract to inadequacies from prior learning, developmental education was needed to provide students with counseling, tutoring, and study skills training along with other needed interventions. The focus on the need for both remedial and developmental education continued to grow into the late 1990s as colleges and universities added more courses and steered underprepared students into these courses in increasing numbers (Damashek, 1999a). As the costs for non college level coursework grew, federal and state legislators began to scrutinize the need for developmental education (Zumeta, 1998). The decade of the 1990s ended with rising costs associated with the added remedial and developmental coursework, with calls for a major paradigm shift from the models of the 1980s and 1990s to a model where learning assistance would be the focus (Damashek, 1999b).

At the turn of the century institutions such as San Francisco State University and state entities such as the Texas Higher Education Coordinating Board began the task of large scale remediation reform. In 2000 the lack of remediation success at San Francisco State University led the institution to redesign its English remediation program by scrapping the prerequisite remediation courses and replacing them with a single course taken over the span of 2 semesters. This course was a combination of a college level English writing course that included the intense reading and writing support needed to successfully complete the college level academic content.

The results were noteworthy, with retention increasing from 88% to 94%, remediation pass rates from 84% to 99%, and with slight gains in reading comprehension and critical reasoning scores as measured by the Descriptive Test of Language Skills post assessment (Goen-Salter, 2008).

As early as 2006 Texas legislators began to take notice of the issues related to the lack of success that developmental education programs were having with their Hispanic population. At the time 20% of America's Hispanic population lived in Texas (Martinez & Martinez, 2006). During the 1990s an average white student requiring remedial studies had a 25% chance of completing a 2-year college degree in a 4-year time period. The completion rates of black and Hispanic students were significantly lower, with those requiring remedial studies having a 10% chance of completing a 2-year degree in the same time frame (Martinez & Martinez, 2006).

Developmental mathematics expert Paul Nolting indicated that adults did not retain mathematics skills as readily as skills in reading and English (Boylan, 2011) because what is learned about basic mathematics, algebra, and other advanced mathematical disciplines is forgotten simply because the skills are not often applied on a daily basis. In the state of Tennessee high school students must take Algebra I, Algebra II, Geometry, and a fourth higher level math course to qualify for graduation, and students must take at least one math course every year (Tennessee Department of Education, n.d.). This change was made for students who were high school freshmen in the fall of 2010 and was implemented to minimize the issue of having students forgetting much of the mathematics content needed to score well on standardized exams (Tennessee Department of Education Consolidated State Application Accountability Workbook, 2010). Adult learners who did not enter college immediately following their graduation from high school often struggle with the ACT Compass exam as well as college level coursework because these critical skills have not been regularly applied since leaving high

school (Wellman & Vandal, 2011). Also, many students who attend community colleges have done so after completing the General Education Development (GED) exam. However, successful completion of the GED exam only requires good arithmetic skills, with no algebra skills needed (Boylan, 2011). Because the four mathematics subscores reported with ACT results are in the areas of pre-Algebra/Elementary Algebra, Intermediate Algebra, Coordinate Geometry, and Plane Geometry/Trigonometry (Preparing for the ACT Test, 2015), it is evident that the GED curriculum will not prepare a student to meet the benchmark scores on the various standardized exams to avoid placement in remedial mathematics.

Part of the concerns regarding the perceived lack of remediation success is the cost that many associate with this lack of success. Saxon and Boylan (2001) cited a 1998 study that projected the annual cost for remedial education nationally to be between \$911 million and \$1.05 billion. Texas reported in 2013 that the state community colleges spent more than \$72 million on remedial education and experienced a 62% dropout rate (Complete College Texas, 2013). Other states reported statistics that are in line with these, and it is data such as these that remediation reformers are using to forward their cause. For example, in the following year, Colorado spent \$47.1 million on remedial education to have 42% of these students fail to return for the following year (Colorado Department of Higher Education, 2015). Nationally the total cost of remediation based on the number of students entering college each year, the historical average of number of remedial courses required by first time students, and the nationwide average tuition cost per credit hour has been estimated to be as high as \$7 billion (Scott-Clayton, Crosta, & Belfield, 2012). Combining these figures with the data showing that 9.5% of community college students needing remediation will graduate within 3 years and 35.1% of 4-year college students needing

remediation will graduate within 6 years (Remediation, 2012), the cause for concern is legitimate.

Some institutions are using such information to justify heavy spending to replace traditional remediation with technology. In 2013 Essex County College in Newark, New Jersey, spent \$1.2 million to outfit two new computerized mathematics labs and selected ALEKS, an adaptive mathematics software package, in hopes of reversing the trend of having only 10% of the college's remedial education students complete a college level math course. Unfortunately, the results to date have not yielded success, leading administrators to theorize that the problem lies with the beliefs and behaviors of the students (Fain, 2015a).

While most educators teaching mathematics in a community college setting are highly skilled in the discipline, many have had not coursework or formal training in developmental education or the application of various learning strategies (Bonham & Boylan, 2011). While a traditional lecture based delivery may be suitable for developmental courses in writing and reading, the same does not hold true for courses in mathematics. Some mathematics remediation experts do not believe developmental mathematics courses require a lecture environment to be successful. They require curricula ripe with manipulatives, study skills, vocabulary skills, and tutoring in order to be effective (Nolting & Nolting, 2008). In short, developmental mathematics should closer resemble a lab with many different types of activities to cover a broad range of student learning styles. By assigning instructors who are flexible and who can adapt their teaching styles to the various student learning styles they encounter through the use of lab based teaching tools, students can find ways to adapt their study strategies to create methods that work best for them (Nolting & Nolting, 2008).

Another issue regarding mathematics remediation is that sequenced courses in the discipline are extremely linear in the fact that the skills learned in a prerequisite course are essential foundations for subsequent courses. According to Johnson and Kuennen (2004) one of the primary goals of mathematics remediation is the development of mathematics skills that are needed in subsequent non mathematics courses. Students who excel in the first course or courses in the sequence typically do well in subsequent courses presumably because they have developed the foundational skills needed at the next level. However, students who do not do well early in the sequence of courses typically make lower grades in subsequent courses because they do not master the content found in prerequisite courses (Boylan, 2011).

In an era of meeting the accessibility needs of students with disabilities, one may assume that such issues are a major contributor to the woes of developmental education. However, in his interview with Boylan, Nolting stated that while learning disabilities and other infirmities are sometimes present among students requiring mathematics remediation, the majority of students who are failing the developmental mathematics courses have no such incapacities (Boylan, 2011).

The Need for Traditional Remediation

Those who advocate remedial education are quick to note that students who take remediation courses are more likely to graduate than equivalent students who do not take these courses (Fain, 2013a). In the early 1980s some states followed a plan in which remediation was optional. As the need for remediation became more evident, states began to develop systematic guidelines that were intended to improve the remediation process (Bader & Hardin, 2002). As more was learned about remediation, it was it became apparent that low-income students, nontraditional students, and students from minority populations are more likely to need the extra

support offered through developmental education (Flannery, 2014). The same can be said for first-generation college students because they experience many of the same problems common to these student populations. Even though remediation in the area of mathematics has proved to be a barrier for many students, research has indicated that students who successfully passed courses that were part of developmental education programs were as successful in subsequent mathematics courses as those students whose entrance exam scores qualified them to skip remediation (Bonham & Boylan, 2011).

The approach of allowing students to opt out of remedial coursework conflicts with many of the beliefs that are prevalent among educational professionals. Many believe that students will not make good choices regarding remediation when they find that these courses are not mandatory (Fain, 2013a). The fear is that students will opt not to take the remedial courses prescribed because of factors other than the need that their standardized course results indicate. As an example, Florida instituted the state's legislation making remediation optional for the fall 2014 semester. Upon completion of the first year of studies under this legislation, the results were concerning. At St. Petersburg College the population of students who followed the recommendation to enroll in mathematics remediation, had a 70.5% pass rate in their college level math courses compared to a 55.3% pass rate for those who chose not to participate in remediation (Smith, 2015c). Proponents for making remediation optional offer data that shows few students will emerge from remedial regimens to graduate. However, Flannery (2014) cited a 2006 study that indicated students who participated in remediation were more likely to graduate than those that do not. While the traditional method of remediation may have its shortcomings, discontinuing it altogether does not appear to be the solution to the problem.

In 1998 the Thomas B. Fordham Foundation released the results of a follow-up study on developmental education that confirmed the costs associated with remediation would project to approximately \$1 billion (Breneman & Haarlow, 1998). When attempting to pinpoint the sources of these costs some professionals believe the effects of remediation education extend outside the classroom. A.W. Astin, a Distinguished Professor Emeritus of Higher Education and Organizational Change at the University of California, Los Angeles, was quoted in a 2015 article as having stated that "providing effective 'remedial' education would do more to alleviate our most serious social and economic problems than almost any other action we could take" (Brinkerhoff & Sorensen, 2015, p. 110). According to Aycaster (2001), "the alternatives to remediation can range from unemployment and low-wage jobs to welfare participation and incarceration, all of which are more expensive for society" (p. 404).

Some states have opted to discontinue developmental education programs at 4-year institutions. State funding for remedial education has been terminated in Oklahoma, Nevada, Colorado, and South Carolina (Jacobs, 2012). Louisiana requires all students whose ACT scores place them in remedial coursework to attend community colleges where they must complete all required remedial coursework before being accepted into a 4-year institution.

Tennessee is among these states that have discontinued remedial education at state universities and requires all remediation be performed at community colleges (Complete College Tennessee Act of 2010, 2010). There are many pros and cons to requiring all remediation to be done at the community college level. Damashek (1999b) presented two opposing viewpoints related to relegating all developmental coursework to the community college. On one hand, many see the community college setting as more effective for offering remedial education than the setting at a 4-year institutions. On the other hand, there are concerns of having students in

need of developmental education commute great distances to attend the nearest community college because typical community colleges lack the resources needed to board students. At the same time, many community college administrators are concerned that operating budgets for remedial programs are being limited by state legislators, who are also legislating the number of courses and credit hours developmental education programs can contain (Fain, 2012). This has community college leadership fearing that state educational leadership will legislate limits on remediation without providing funding for the extra resources that will be expended to remediate those who once received the remedial coursework at the 4-year institutions.

Discontinuing developmental education at some 4-year institutions may have merit. Boylan (1995) voiced his opinion that major universities such as Harvard, Stanford, Colgate, and smaller private schools probably did not need developmental education programs because of their admissions standards. However, as state universities came under consideration, the competitiveness in admissions declined, making the need for remedial programs more difficult to dismiss (Boylan, 1995). In 2015 the state of Maryland released the results of a study that indicated that students were more likely to successfully complete remediation courses taken in the community colleges than if taken at a state 4-year institution (Department of Legislative Services, Office of Policy Analysis, 2015). This study also determined that the cost savings would be significant, as the tuition and fees at the community college level was substantially lower than those same fees at the 4-year institutions.

The strongest evidence that can be provided in support of traditional remediation lies in the reason for the need being tied to the unpreparedness of students entering college. The need for remediation is not a new concept, as the nation's first educational department focused solely on remediation was created in 1849 and the University of Wisconsin (Boylan, 1988). This

department was created due a sudden influx of students who could afford the cost of higher education but were underprepared for the academic rigor of higher education. Before the Emancipation Proclamation of 1863 there were only two colleges in existence that were chartered to provide higher education to black students (Jones & Richards-Smith, 1987). Prior to this event there was no formal structure for the education of black people. However, after the Civil War ended and opportunities for education were opening for black people, the number of unprepared black students seeking admission to colleges rose drastically, and remediation was instituted to meet the needs of these students. During the 20th century the widespread adoption of open enrollment policies in the 1960s and the 1970s coupled with the passage of the Civil Rights Act of 1964 and the Higher Education Act of 1965 created the means for more high school graduates to attend college (Phipps, 1998), which further increased the numbers of students who had not been sufficiently prepared for college level work. In these instances can be found the basic idea of remedial education; it is the supposition that “most academically deficient students do not lack talent. They lack preparation” (McCabe, 2003, p. 7). In 1984, Tennessee’s State Board of Regents prepared a white paper to lay the groundwork for the formalization of a remediation program to be implemented across the state (The State Board of Regents, 1984). In this manuscript the board emphasized that:

underpreparedness does not equate with being incapable or ineducable; the causes of underpreparedness are multiple and complex; some underpreparedness results from changing social and economic conditions—factors over which schools and students have no control; everyone has a right to a ‘second chance’ and, indeed, is cost-effective for the state to provide ‘second chances’ for the educationally disadvantaged whatever the causes. (p. 36)

As more opportunities for high school graduates to attend college have emerged through the years, increasing numbers of students have been entering college unprepared for college level work, and proponents of traditional remedial education have been using these data to justify the need to keep the current remediation models in place.

Reformation of Traditional Remediation

Researchers have presented evidence dating back to the 1950s that indicated the use of stand-alone developmental courses in reading and writing seldom improve student academic skills and do not prepare them for college level coursework (Damashek, 1999a). At the beginning of the 2000 academic year the average number of remedial mathematics courses offered at public 2-year colleges was 3.6 (Bailey, Jeong, & Cho, 2010). A later study found that most colleges that provide remedial coursework offer between two and three levels of developmental mathematics courses (Biswas, 2007). One of the issues cited by CCA is the time it takes for students requiring remediation to complete not only the remediation regimen but to follow up with completing their college level degree requirements (Corequisite Remediation, n.d.). Roughly 60% of community college students annually require remediation. Of this group 10% will complete a 2-year degree in 3 years (Jones, 2014). Institutions with multiple remedial courses results in many students being required to enrolled in these courses over the course of several semesters. Evidence shows that persistence to completing the final course in remediation sequences that allowed students to proceed to college level courses was inversely proportional to the course level at which they were required to begin (Guy, Puri, & Cornick, 2015). It was for this reason that North Carolina and Virginia colleges redesigned their remedial education models to improve student success (Kalamkarian, Raufman, & Edgecombe, 2015). Their data indicated that the average student needed roughly three courses in their previous model to meet their remedial

education needs. As a result of the number of courses being required, many students failed to finish the remediation regimen and would drop out of college because of additional time and added costs associated with remediation under their former models (Augenblick, Palaich, & Associates, Inc., 2012).

These effects that multiple course developmental education programs have on student retention and graduation have led the drive toward corequisite remediation. Data published by CCA indicated that students who are enrolled in corequisite math courses that were associated with the college level math courses required in their degree major were five to six times more likely to succeed than students who followed a traditional developmental education sequence of courses (The results are in, 2015). Asera (2011) stated that the most effective remediation models were those that deeply engaged the students with concentrated and rigorous content. Closely associated with this issue is the problem that reformers refer to as a mismatch between not only developmental mathematics courses and college level mathematics courses, but between mathematics courses and the science courses that require mathematics courses as prerequisites. Often, faculty find themselves teaching mathematical concepts that students are expected to have mastered in prerequisites coursework (Burn, Baer, & Wenner, 2015). Such issues have spawned the concept of embedded mathematics remediation.

The Corequisite Remediation Movement

CCA has been at the forefront of remediation reform. The organization has secured agreements with legislators in 33 states plus the District of Columbia to agree to pursue the organization's goals of increasing the number of Americans with postsecondary certifications or degrees and closing the attainment gap for ethnic minority populations and those populations of students who can be considered financially underprivileged (Fain, 2012). By entering into this

partnership, these entities have agreed to implement systemic reforms within their institutions of higher education, using the five principles advocated by CCA. These principles, called “Game Changers” by the organization (Game Changers, n.d.). The two most important principles related to this work are performance funding and corequisite remediation. CCA’s plan for performance funding is to require portions of state funding to be tied to all public institutions based on each institution’s success at improving measurements related to the two-fold goals of the organization. The second principle, corequisite remediation, requires the creation of coursework designed to be taken alongside college level courses, thus replacing prerequisite models.

The application of corequisite remediation in place of a multiple course remediation regimen obviously allows students to shorten the number of semesters needed for degree completion by eliminating the number of semesters required for sequential course completion. However, corequisite remediation must be more than compressing content and changing curricula to meet scheduling goals (Reimagining Remediation in Tennessee, 2015). It must be designed to provide educational content and support needed for the college level course with which the curriculum is paired. During the 2009/2010 academic year the Carnegie Foundation for the Advancement of Teaching introduced two revolutionary pathways for developmental mathematics education. These two pathways were named Statway and Quantway (Merseth, 2011).

Statway is a year-long statistics course with the necessary remediation required for the discipline embedded into the course. When students complete this course, they receive credit for a college level statistics course (Merseth, 2011). Quantway is a course that teaches students to solve real-world problems using mathematics (Long, 2015). Development began with the intent to create a one-semester quantitative reasoning course. However, the group quickly discovered that a second follow-up course would be required (Merseth, 2011).

The issues the team was having in creating a single quantitative reasoning course can be explained by the results of a survey published in 2006 by the American Institutes for Research. This survey measured the literacy of college students in three disciplines: prose literacy, document literacy, and quantitative literacy. Of these three the discipline students struggled with the most was quantitative literacy (Baer, Cook, & Baldy, 2006). It must be understood that both the Statway and Quantway models are intended for students whose majors fall outside the realm of Science, Technology, Engineering, and Mathematics (STEM), as the academic rigor of these courses are ineffective in preparing students for study in these areas (Merseth, 2011).

The success of the Carnegie Foundation remediation programs has been noteworthy. Twenty-one colleges using the Statway program were assessed in 2012, and results showed that not only did the number of remedial students earning college level math credit triple, they did so in half the time based on national averages (Mangan, 2013b). The results from the Quantway program are no less impressive as 56% of the students at institutions participating in the Quantway program during the 2012 academic year completed their remediation coursework in a single semester, whereas previous models would have required a similar percentage of students a full academic year to complete (Collins, 2013).

Other states have adopted different models that have also been successful. North Carolina and Virginia took the approach to remedial education of abandoning semester-long courses in favor of shorter modules lasting a fraction of a full semester that are more focused on specific content (Augenblick, Palaich, & Associates, Inc., 2012). Both states also created new mathematics assessments that were customized to provide current snapshots of the students' academic skills as well as pinpoint specific areas of mathematics remediation that are required

based on each student's intended major. These assessments are being used in place of other commonly used standardized exams (Augenblick, Palaich, & Associates, Inc., 2012).

In 2010 Florida began using a new assessment to determine college readiness. The Postsecondary Education Readiness Test, or PERT, was created by faculty from various levels of the education system and for the purpose of replacing the Accuplacer assessment (Augenblick, 2012). PERT is not only being used as a placement assessment in all the state's community college, it is also being used for all high school 11th graders who did not meet the minimum scores on the statewide standardized student examination as a means of developing a better understanding of individual academic issues (Augenblick, Palaich, & Associates, Inc., 2012).

Not only has Florida changed the manner in which the state assesses the college readiness of incoming freshmen, state legislators have taken a bold step in the area of remediation requirements. In 2013 Florida legislators signed into law State Bill 1720, making standardized placement exams and remediation courses for traditional community college students optional (Fain, 2013a). Nontraditional students entering community colleges were still required to take an assessment to determine college level course readiness. and if the benchmark scores were not met, they were required to take an online corequisite remediation course (Flannery, 2014). The results of this law have not only affected enrollment in remedial courses, but the success rates of students in college level courses has also been affected. Evidence indicates that most students who are given the choice to opt out of developmental coursework have done so (Mangan, 2015). Without proper advising regarding the needs for some students to opt for remediation, most traditional students will choose the path they perceive will be the easiest to complete (Fain, 2013a). Following the 2014 academic year Miami-Dade College released information that,

following the enactment of this law, registration for developmental mathematics courses fell by 42% (Smith, 2015c).

In 2015 the state of Florida also released the academic results of its remediation optional program. At St. Petersburg College the success rate of students who participated in developmental mathematics courses was 70.5% compared to the 55.3% success rate of those who did not. Of the students who opted to skip developmental coursework and take college level math against the recommendations of college advisors to take the developmental equivalent, only 20% passed with a grade of C or better. At Miami-Dade College the pass rate for gateway mathematics courses also fell from 55.7% to 46.8%. It was also revealed that success rates at both institutions declined as the number of developmental courses skipped increased (Smith, 2015b).

Florida is not the only state that has been caught up in remediation reform. Colorado, Connecticut, Indiana, Tennessee, and West Virginia have adopted corequisite remediation models for the 2015 academic year (Smith, 2015b). Minnesota, Montana, and Nevada are considering legislation of their own.

Tennessee has also had some success partnering with high schools to allow students the opportunity to remediate in the area of mathematics during their senior year of high school. Community colleges across the state began partnering with local high schools as part of a project entitled the Seamless Alignment and Integrated Learning Support (SAILS) program. This program allows high school students whose ACT scores on the mathematics section of the exam do not meet the minimum score of 19 needed for placement into college level mathematics courses to complete their remediation requirements while still in high school. To date the project

has shown success, but not enough data exist to gauge its effectiveness of student performance in subsequent college level mathematics courses (Fain, 2013a).

Though the idea is not necessarily new, the application of student support courses is regaining momentum. One study in particular, conducted during the 2008 academic year at a community college in Ohio, concluded that first year experience courses taught by trained counselors were particularly effective among Black and Latino students in regard to academic success in both developmental and college level coursework (Barnes, 2012).

While corequisite remediation works well for many whose ACT test scores were within a point or two from institutional cutoff scores, those whose scores deviated more from the cutoff score were often less successful, as the differences between the actual scores and cutoff scores were indicative of a greater level of need (Mangan, 2015).

Chapter Summary

Developmental education is a critical aspect of higher education, as there are significant percentages of high school graduates and adult learners returning to college who are not prepared for the rigors of higher education academics. The purpose of developmental education is to provide the critical skills needed in the areas of English, reading, and mathematics that these potential students did not adequately learn while in high school and to refresh skills that have diminished over time and through a lack of application. There is a need to assess these skills for each potential student and, while standardized testing may have shortcomings, no better substitute has materialized. There are data in existence supporting the idea that non-academic factors exist that can affect the success of students needing remediation (Lotkowski et al., 2004). However, it is difficult to quantify these factors in a way that can be used to predict the levels and types of nonacademic support each student needs for success.

There are many who question the success of traditional remediation practices, in part because no significant increases in the percentages of students completing remediation coursework and percentages of those continuing through degree completion in what some consider an acceptable time frame have been realized. Remediation is seen by many as a barrier to obtaining postsecondary credentials. Many students place a negative stigma on developmental education and, when faced with multiple semester sequences of developmental courses, many become discouraged and do not register for courses because traditional remediation increases the number of semesters needed in order to complete degree requirements beyond what they consider a reasonable time frame.

Corequisite remediation is seen by many as the best practice for providing the support students need in a real-time environment, allowing students to complete both remedial and college level courses more expeditiously, which many expect will increase retention and graduation measures. The area of mathematics is of particular concern, as more students are placed in mathematics remediation than any other subject area. Some believe corequisite remediation will not adequately prepare students to apply the mathematics covered in the corequisite sequence in subsequent courses, especially those in areas like natural sciences where strong mathematics skills are essential to success.

There is no single best practice. Many believe that multiple models are needed to meet the varying needs of traditional students versus the needs of the adult learner. Many also believe that, depending on standardized placement exam scores, that corequisite remediation may be best suited for students whose scores were just below the established cutoff benchmarks, while students with lower scores may require more support than a corequisite model can offer. By comparing various remediation models, it is the purpose of this study to identify best practices in

developmental mathematics remediation in general as well attempt to determine the feasibility of applying multiple models based on differences in student populations.

CHAPTER 3

RESEARCH METHODOLOGY

The purpose of this study was to determine if there are significant differences between four mathematics learning support models based on student performance in two college level mathematics courses at a 2-year community college in Tennessee. Over one half of the high school graduates entering community colleges require remediation in at least one subject area and, of this number, less than one fourth will complete their remediation courses along with the related college level courses within 2 academic years (Games Changers, n.d.). Of those who complete their remediation and related college level coursework within a 2-year period, roughly 1 in 10 will complete their 2-year degree requirements by the end of their third academic year (Corequisite Remediation, n.d.). Because all requirements for prerequisite remediation having been removed from the 4-year institutions in the state of Tennessee, combined with a heightened emphasis on retention and graduation measurements as they are being applied to performance funding measurements, Tennessee's community colleges must find ways to effectively remediate the larger populations of students who are arriving on their campuses requiring remediation to help prepare them to succeed academically at a collegiate level. The Tennessee Board of Regents mandated that all community colleges propose and implement corequisite remediation models in the areas of writing, reading, and mathematics beginning in the fall of 2015 (Reimagining Remediation in Tennessee, 2015). At the inception of this study, no evidence existed on which reliable conclusions could be drawn relative to the expected success of corequisite remediation as implemented by the state's community colleges. While more effective remediation is needed in the areas of English composition, reading, and mathematics, data show the subject of mathematics as being the most often cited barrier related to student success in developmental education (Bonham & Boylan, 2011).

This study was conducted at Walters State Community College in Morristown, Tennessee, an institution governed by the Tennessee Board of Regents. This institution serves a 10-county area with a population exceeding 435,000 residents (Walters State Community College Fact Book, 2014). The majority of the students attending this institution are local to the area, as there are no boarding accommodations on the campus. More than half the students entering this institution as first-time freshmen will have scored below a 19 on the mathematics section of the ACT exam, requiring them to enroll in mathematics remediation courses. This study was focused on comparing four separate mathematics remediation models that have been used since the beginning of the fall semester of 2011. The four models include a three-course regimen totaling nine semester hours, a five-course regimen totaling five semester hours, a five module course taught to high school seniors, and the current three semester hour corequisite course taught alongside a college level course.

A quantitative analysis was chosen for this study because the student performance levels that were related to the problem statement were categorical in nature, and thus nominal data were archived in the student records database. The purpose of this study was to determine if there were significant differences between four mathematics learning support models based on student performance in two college level mathematics courses at a 2-year community college in Tennessee. The two college level mathematics courses chosen for this study were MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics. These courses were chosen for three reasons. First, students not majoring in STEM (Science, Technology, Engineering, and Mathematics) programs were likely to be required to take one of these two courses instead of precalculus or calculus courses for their required general education mathematics course. This resulted in the majority of students enrolling in these two courses. Second, these two courses

were consistent offerings in the mathematics division and can be related to remedial courses across the span of time this study involved. Finally, these were two of three courses paired with corequisite learning support mathematics courses in the current corequisite remediation model. The experiment was a causal-comparative design. Also referred to as an ex post facto design, a causal-comparative design is a comparative study that allows the experimenter to draw causal conclusions when the data already exist (McMillan & Schumacher, 2010). Because the independent variable of student letter grades in the two aforementioned college level mathematics courses was drawn from archival data, the causal-comparative design was the best option for data analysis. Such archival data prevented the random assignment of groups and did not allow the variables to be manipulated beyond the groupings that were used for comparison.

Research Questions and Null Hypotheses

The premise of remediation at the college level is to ensure that students who have been deemed underprepared for college level work obtain the knowledge necessary to successfully complete college coursework in the subject areas where remediation needs have been identified. To this end, there were several research questions that were addressed in this study to determine if significant differences existed between mathematics remediation models as determined by the performance of students in college level mathematics courses. Research questions 1 and 2 were to study the effects of the four Learning Support models on statistics based and algebra based quantitative reasoning courses.

Research questions 3 and 4 were to study the effects of the four Learning Support models on student success in college level mathematics courses for students whose ACT mathematics exam scores were a 17 or an 18. For students who took the SAT exam or the Act Compass exam, the equivalent scores for the mathematics sections of these exams were factored into the study.

These scores were selected for these two questions because they would have placed students into the highest level Learning Support course in the LS1 model.

Research questions 5 and 6 were to study the effects of the four Learning Support models on student success in college level mathematics courses for students whose ACT mathematics exam scores were a 15 or a 16. For students who took the SAT exam or the Act Compass exam, the equivalent scores for the mathematics sections of these exams were factored into the study. These scores were selected for these two questions because they would have placed students into two of the three Learning Support courses that comprised the LS1 model.

Research questions 7 and 8 were to study the effects of the four Learning Support models on student success in college level mathematics courses for students whose ACT mathematics exam scores were lower than 15. For students who took the SAT exam or the Act Compass exam, the equivalent scores for the mathematics sections of these exams were factored into the study. These scores were selected for these two questions because they would have placed students into all three of the Learning Support courses that comprised the LS1 model.

Research questions 9 and 10 were to study the effects of the four Learning Support models on student success in a college level probability and statistics course based on the categorized age of the students. Students who were under the age of 25 at the time they took the probability and statistics course were classified as traditional students, while those 25 and older were classified as nontraditional students.

Research questions 11 and 12 were to study the effects of the four Learning Support models on student success in a college level algebra course based on the categorized age of the students. Students who were under the age of 25 at the time they took the college algebra course

were classified as traditional students, while those 25 and older were classified as nontraditional students.

Research questions 13 and 14 were to study the effects of the four Learning Support models on student success in a college level probability and statistics course based on the course load of the students. Students who were enrolled in under 12 semester hours were classified as part-time students, while those enrolled in 12 or more semester hours were classified as full-time students.

Research questions 15 and 16 were to study the effects of the four Learning Support models on student success in a college level algebra course based on the course load of the students. Students who were enrolled in under 12 semester hours were classified as part-time students, while those enrolled in 12 or more semester hours were classified as full-time students.

The four Learning Support models were identified in this study as Learning Support Model 1 (LS1), Learning Support Model 2 (LS2), Learning Support Model 3 (LS3), and Learning Support Model 4 (LS4). Learning Support Model 1 consisted of three courses, each having three semester hours' credit. This model was in use during the 2011 and 2012 academic years. Students whose mathematics scores on the ACT exam were 15 or less were required to begin with the basic mathematics course and then progress through the elementary algebra and intermediate algebra courses before being allowed to register for college level mathematics courses. Students whose SAT mathematics scores were below 350 and students whose ACT Compass scores were below 21 were also required to begin with the basic mathematics course.

Learning Support Model 2 was used during the 2013 and 2014 academic years. This model consisted of five courses of one credit hour each. All students whose ACT mathematics scores were below the cutoff score of 19 were required to take these courses. Students whose

SAT mathematics scores were below 600 and students whose ACT Compass scores were below 38 were also required to complete these five courses before being allowed to register for college level mathematics courses.

Learning Support Model 3 was initiated in the fall of 2015. This model featured one course with three credit hours that was required to be taken concurrently with one of three college level mathematics courses. MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, were the two courses that were included in this study due to the volume of students enrolled in these courses. The third course was designed only for those students who were going to major in STEM fields and were required to take developmental mathematics courses. STEM majors typically do not require remediation, so the number of students who take this course was low. Students whose ACT mathematics scores were below 19, along with students whose SAT mathematics scores were below 600 and students whose ACT Compass scores were below 38 were required to register for this Learning Support course along with one of the corequisite college level mathematics courses prescribed.

Learning Support Model 4 was a program entitled Seamless Alignment and Integration of Learning Support, abbreviated SAILS. This program was designed to provide mathematics remediation to high school seniors before graduation. The SAILS program was introduced into area high schools in the fall of 2013, with the first students completing this program entering Walters State during the fall 2014 semester. The SAILS model was patterned after the college's LS2 model, and students who successfully completed all five modules were considered by the college to have completed their remediation requirements.

The research questions included in this study were:

1. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who participated in learning support models LS1, LS2, LS3, or LS4?

Ho1: There is no significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who participated in learning support models LS1, LS2, LS3, or LS4.

2. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who participated in learning support models LS1, LS2, LS3, or LS4?

Ho2: There is no significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who participated in learning support models LS1, LS2, LS3, or LS4.

3. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?

Ho3: There is no significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4.

4. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?

Ho4: There is no significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4.

5. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the

mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?

Ho5: There is no significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4.

6. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?

Ho6: There is no significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4.

7. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored less than

15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?

H₀₇: There is no significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4.

8. Is there a significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4?

H₀₈: There is no significant difference in the proportion of students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, and LS4.

9. Is there a significant difference in the proportion of traditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final

course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4?

Ho9: There is no significant difference in the proportion of traditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4.

10. Is there a significant difference in the proportion of nontraditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, and LS3?

Ho10: There is no significant difference in the proportion of nontraditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, and LS3.

11. Is there a significant difference in the proportion of traditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, and LS4?

Ho11: There is no significant difference in the proportion of traditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, and LS4.

12. Is there a significant difference in the proportion of nontraditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, and LS3?

H₀12: There is no significant difference in the proportion of nontraditional age students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, and LS3.

13. Is there a significant difference in the proportion of full-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4?

H₀13: There is no significant difference in the proportion of full-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4.

14. Is there a significant difference in the proportion of part-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4?

H₀14: There is no significant difference in the proportion of part-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final

course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, and LS4.

15. Is there a significant difference in the proportion of full-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, and LS4?

H_{015} : There is no significant difference in the proportion of full-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, and LS4.

16. Is there a significant difference in the proportion of full-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, or LS4?

H_{016} : There is no significant difference in the proportion of full-time students who are successful (a final course grade of A, B, or C) and who are not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, or LS4.

Population

The participants in this study were students enrolled in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, from the fall semester of 2011 through the end of the spring semester of 2016 and had participated in one of the four learning support models being evaluated in this study. Access to the required data was provided by the Office of

Planning, Research, and Assessment at Walters State Community College following approval by the Institutional Review Board (IRB). To insure subject anonymity all personal identifiers were coded in such a way as to ensure compliance with the IRB policies and guidelines. Once the coded data were supplied, records containing ACT, SAT, or ACT Compass scores that exceeded the benchmark scores (19, 460, and 37, respectively) were removed, as these students were not required to participate in learning support courses. Records containing the letter grade “W” were also removed, as student withdrawals were not included in the scope of the study. Multiple records with the same coded identifier were located and marked. Multiple records with the same coded identifier indicated multiple attempts to pass one of the two courses. Because the scope of the study was to evaluate student success in the first attempt for these courses, the earliest records were retained, and the remaining records deleted from the dataset. After the dataset was purged of irrelevant records, 4,304 records remained.

Data Collection

The information needed for this study included letter grades awarded to students participating in either MATH 1530, Probability and Statistics, or MATH 1630, Finite Mathematics, beginning in the fall 2011 semester and continuing through the spring 2016 semester. Because the intent of this study was to measure the impact of student learning support on college level course grades, only the first grades for students taking the courses multiple times were used. The final course grades were grouped, combining the letter grades of A, B, and C into one group and grades D and F into a second group. The criteria for course transferability, as well as admission into many competitive A.A.S. programs, is often a grade of C or higher, which explains the logic behind the course grouping. For all of these students mathematics scores from their placement exams were needed, as well as all mathematics remediation courses taken, if

applicable, so the remediation model used could be identified. The age of each student and attendance status of each student (full-time versus part-time) was also required. The institution determined that this was a viable study, and the results have the potential of providing critical insight into understanding the remediation needs of students. Because of this the institution's Office of Planning, Research, and Assessment agreed to gather the data and code each student record in a way that ensured student anonymity before making it available to the researcher.

Data Analysis

Each of the research questions was analyzed using quasi-experimental methods. The data for each of the research questions were analyzed using chi-square tests of independence. Two-way frequency tables were used on each research question to analyze the effects of various mathematics remediation models with respect to student success in college level mathematics courses. All data were analyzed at the 0.05 level of statistical significance. Pairwise comparisons were used to research question results that indicate statistical significance, with the application of the Holm's Sequential Bonferroni method to control the Type I error at the .05 level of statistical significance across the pairwise comparisons conducted. IBM-SPSS software was used to analyze all data for the study.

Chapter Summary

Chapter 3 of this study presented the research method that was used in efforts to address the problem statement relative to the application of various learning support mathematics models that have been used at Walters State Community College in recent years. This chapter identified the population of students whose archival data was used for the study and listed again the research questions along with the null hypotheses for each question. The chapter also described

how the archival data were collected and the means by which the data were studied. The chapter ended with a summary of the chapter's contents.

CHAPTER 4

FINDINGS

According to the 2014-2015 Tennessee Higher Education Fact Book (2015), the percentage of high school graduates who entered college ranged from 55.7% in 2009 to 58.1% in 2013. From 2010 through 2014 the average ACT composite score for Tennessee's high school students ranged between 19.5 and 19.8 (Garrison, 2014). ACT has established benchmark scores for the four exam subject areas, an 18 in English, a 22 for reading and mathematics, and a 23 in science (ACT, n.d.). ACT advertises that students who meet or exceed benchmark scores in subject areas have a 50% chance of earning a letter grade of B or better in their college level coursework in the respective subject area and a 75% percent chance of earning a letter grade of C or better (ACT profile report – state: Graduating Class 2015 Tennessee, 2015). According to Garrison (2014) only 19% of Tennessee's high school students meet or exceed the ACT benchmark scores in all four subject areas. In 2015 the average score on the mathematics section of the ACT for Tennessee high school students was 19.2 (ACT profile report – state: Graduating Class 2015 Tennessee, 2015). According to the ACT profile report only 30% of Tennessee students meet or surpass the mathematics benchmark, the lowest percentage of any subject area for which remediation is provided. TBR has established an ACT cutoff score of 19 in the area of mathematics as the threshold for remediation requirements (Tennessee Board of Regents, 2012), far below the ACT recommended benchmark of 22. It is evident that a large population of Tennessee's high school graduates enter college underprepared for college level mathematics.

Remedial education in Tennessee was formally introduced in 1984 (The State Board of Regents, 1984) to address the needs of underprepared students entering the state's colleges and universities. From its inception until the turn of the century, Tennessee's remediation program

underwent several changes in courses and course sequences among the various state higher education institutions (Bader & Hardin, 2002). These courses and sequences have always required students to complete a prerequisite remediation regimen before they were allowed to register for college level coursework. Many detractors of prerequisite remediation models cite statistics that indicate less than 30% of community college students requiring remediation will complete their degree requirements in 3 years, claiming students with multiple prerequisite remediation courses become frustrated and withdraw from college before completing their degrees (Remediation, 2012) Attempts to reduce the time required to complete a prerequisite remediation regimen began in the fall semester of 2013 when TBR mandated that remedial mathematics was to be accomplished in modularized courses, with each course being limited to one credit hour each (Tennessee Board of Regents, 2012). Beginning in the fall semester 2015 mathematics remediation in TBR institutions again changed, dropping all prerequisite coursework in favor of a single course to be taken as a corequisite support course for one of three college level mathematics courses. Therefore, the purpose of this study is to determine if there were significant differences among four mathematics learning support models based on student performance in two college level mathematics courses at a 2-year community college in Tennessee.

This study was designed to compare four different mathematics remediation models that have been in use since the fall semester of 2011. Student success was defined by the letter grades earned in two courses, and these letter grades were the foundation for this comparative study. The two courses selected were MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics. These were chosen because the courses have been the preferred general education mathematics courses for most of the college's degree programs and have remained consistent in

both content and student learning outcomes over the time frame spanned by the study. These courses were and are currently also the predominant courses to which corequisite remediation courses were and are currently assigned.

Another consideration of this study was the level of preparation of each student entering the institution. Placement into remedial coursework is determined by entrance exam scores. The exams used by the students in this study were the ACT exam, the SAT exam, and the ACT Compass exam. Only the mathematics section scores were considered, and the scores were grouped based on the placement process used with Learning Support Model 1. Also considered were student age and full-time or part-time status. Table 1 shows the student demographic information of the study population.

Table 1

Demographics of Population (n = 4,304)

Variable	Levels	# of Subjects	% of Subjects
College level Math Course	Probability and Statistics	3,092	71.8
	Finite Mathematics	1,212	28.2
Learning Support Model	LS1	2,376	55.2
	LS2	773	18.0
	LS3	797	18.5
	LS4	358	8.3
ACT Score Grouping	17-18	1,853	43.1
	15-16	1,673	38.9
	<15	778	18.0

Table 1

Demographics of Population (n = 4,304) (continued)

Variable	Levels	# of Subjects	% of Subjects
Student Success	Successful (Grade of A, B, or C)	2,433	56.5
	Not successful (Grade of D or F)	1,871	43.5
Enrollment Status	Enrolled Full-time	2,958	68.7
	Enrolled Part-time	1,346	31.3
Student Age	Traditional Age (<25)	3,333	77.4
	Nontraditional Age (≥ 25)	971	22.6

The data for this study were stored in the institution's Banner Software System database. The population of students included all students who completed either MATH 1530, Probability and Statistics, or MATH 1630, Finite Mathematics, during the fall semester of 2011 and continuing through the spring semester of 2016 and had also participated in one of four Learning Support models to satisfy remediation requirements as determined by college entrance exam scores. The data were retrieved by the Office of Planning, Research, and Assessment. After being purged of all personal identifiers to insure subject anonymity, the data were provided to the researcher.

Sixteen research questions were developed to guide the study, and the 16 corresponding null hypotheses were tested. Chi-square tests were used to test each hypothesis to determine if significant differences existed in the student success (letter grades of A, B, or C) in the Math 1530, Probability and Statistics, and the MATH 1630, Finite Mathematics courses based on the learning support model used. The research questions, null hypotheses, and data analyses are presented below.

Research Question 1

Is there a significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who participated in learning support models LS1, LS2, LS3, or LS4?

Ho1: There is no significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of students who were successful and who were not successful in MATH 1530, Probability and Statistics, varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related, Pearson $\chi^2(3, N = 3,092) = 79.44, p < .001$, Cramer's $V = .16$. Therefore, the null hypothesis was rejected.

Table 2 indicates the percentage of students in each grade group by learning support model. Figure 1 shows the count of the number of students in each grade group by learning support model.

Table 2

MATH 1530 Students Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	61.2	57.8	41.2	49.0
Not Successful	38.8	42.2	58.8	51.0
Total	100%	100%	100%	100%

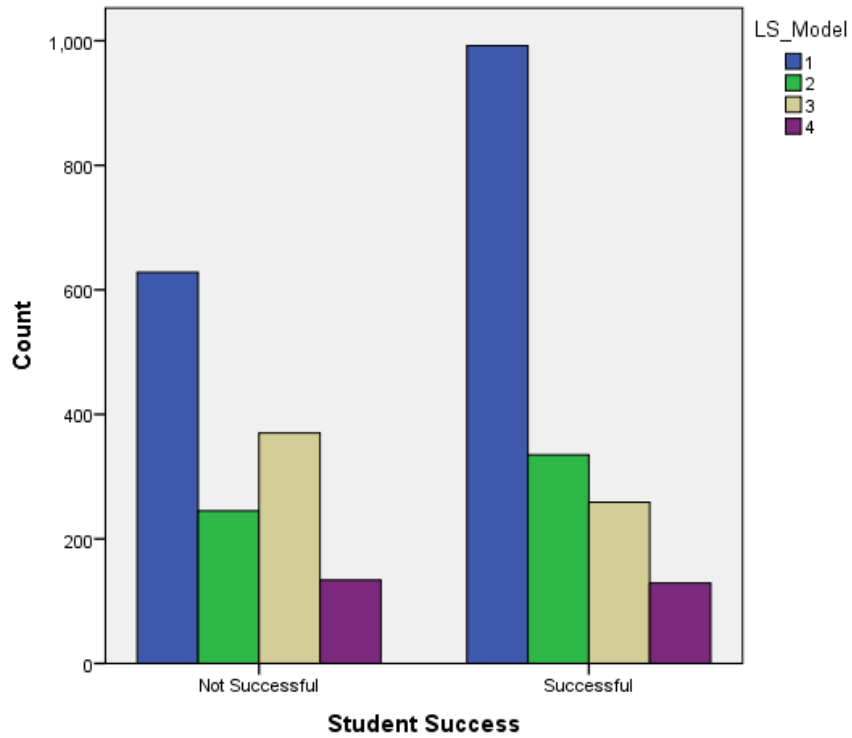


Figure 1 MATH 1530 students in each grade group by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 3 shows the results of these analyses. The Holm’s sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted. In general student success was significantly different between those participating in LS Model 1 (61.2%) vs. LS Model 3 (41.2%), between LS Model 1 (61.2%) vs. LS Model 4 (49.0%), and between LS Model 2 (57.8%) vs. LS Model 3 (41.2%), with models LS1 and LS2 being more successful than models LS3 and LS4. Also, the differences between LS Model 2 (57.8%) vs. LS Model 4 (49.0%) and LS 3 Model (41.2%) vs. LS 4 Model (49.0%) were not statistically significant but displayed a relatively large difference in student success, with model LS4 being more successful.

Table 3

Pairwise Comparison Using the Holm’s Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer’s <i>V</i>
LS1# vs. LS3	73.85*	<.001 (.008)	0.18
LS2# vs. LS3	33.12*	<.001 (.010)	0.17
LS1# vs. LS4	13.95*	<.001 (.013)	0.09
LS2 vs. LS4	5.56	.019 (.017)	0.08
LS3 vs. LS4	4.68	.030 (.025)	0.07
LS1 vs. LS2	2.16	.140 (.050)	0.03

most successful model

**p* value ≤ alpha

Research Question 2

Is there a significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who participated in learning support models LS1, LS2, LS3, or LS4?

Ho2: There is no significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of students who were successful and who were not successful in MATH 1630, Finite Mathematics, varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related, Pearson $\chi^2(3, N = 1,212) = 13.14, p = .004$, Cramer's $V = .10$. Therefore, the null hypothesis was rejected.

Table 4 indicates the percentage of students in each grade group by learning support model. Figure 2 shows the count of the number of students in each grade group by learning support model.

Table 4

MATH 1630 Students Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	62.3	59.6	47.6	54.7
Not Successful	37.7	40.4	52.4	45.3
Total	100%	100%	100%	100%

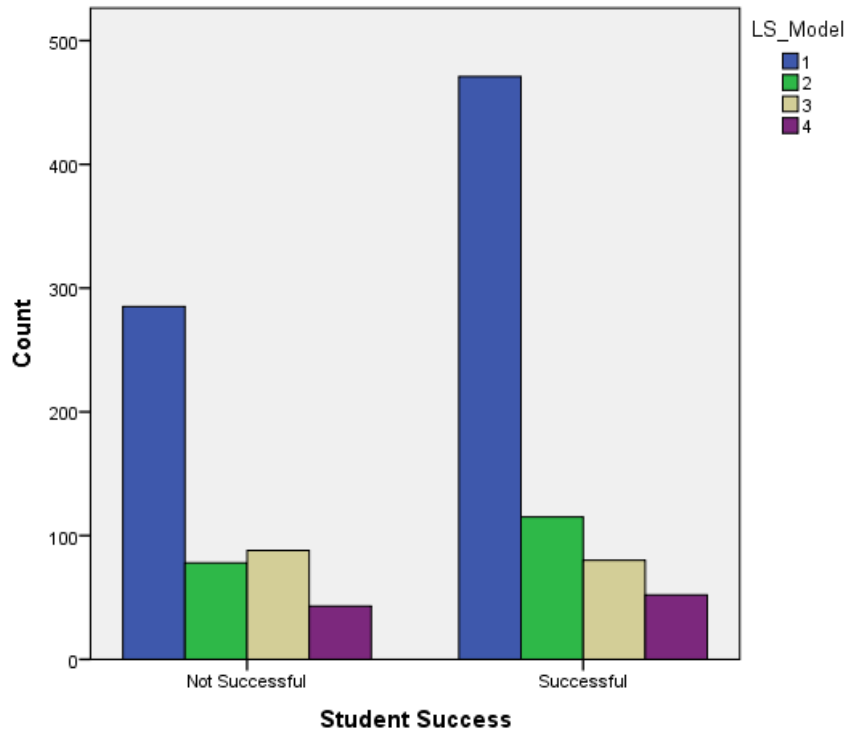


Figure 2 MATH 1630 students in each grade group by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 5 shows the results of these analyses. The Holm’s sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted.

In general, student success was significantly different between those participating in LS Model 1 (62.3%) vs. LS Model 3 (47.6%), with model LS1 being more successful. Also, LS Model 2 (59.6%) vs. LS Model 3 (47.6%), LS Model 1 (62.3%) vs. LS Model 4 (54.7%) and LS Model 3 (47.6%) vs. LS Model 4 (54.7%) were not statistically significant but did display a relatively large difference in student success, with models LS1 and LS 2 being more successful than Models LS 3 and LS4, and model LS4 being more successful than LS3.

Table 5

Pairwise Comparison Using the Holm’s Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer’s <i>V</i>
LS1# vs. LS3	12.31*	<.001 (.008)	.12
LS2 vs. LS3	5.18	.023 (.010)	.12
LS1 vs. LS4	2.04	.153 (.013)	.05
LS3 vs. LS4	1.23	.267 (.017)	.07
LS2 vs. LS4	.61	.433 (.025)	.05
LS1 vs. LS2	.48	.488 (.050)	.02

most successful model

**p* value ≤ alpha

Research Question 3

Is there a significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4?

Ho3: There is no significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of students who were successful and who were not successful in MATH 1530, Probability and Statistics, and scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related, Pearson $\chi^2(3, N = 1,343) = 41.35, p < .001$, Cramer's $V = .18$. Therefore, the null hypothesis was rejected.

Table 6 indicates the percentage of students in each grade group by learning support model. Figure 3 shows the count of the number of students in each grade group by learning support model.

Table 6

MATH 1530 Students Scoring 17 or 18 on the Mathematics Section of the ACT Exam Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	64.1	59.0	40.5	56.9
Not Successful	35.9	41.0	59.5	43.1
Total	100%	100%	100%	100%

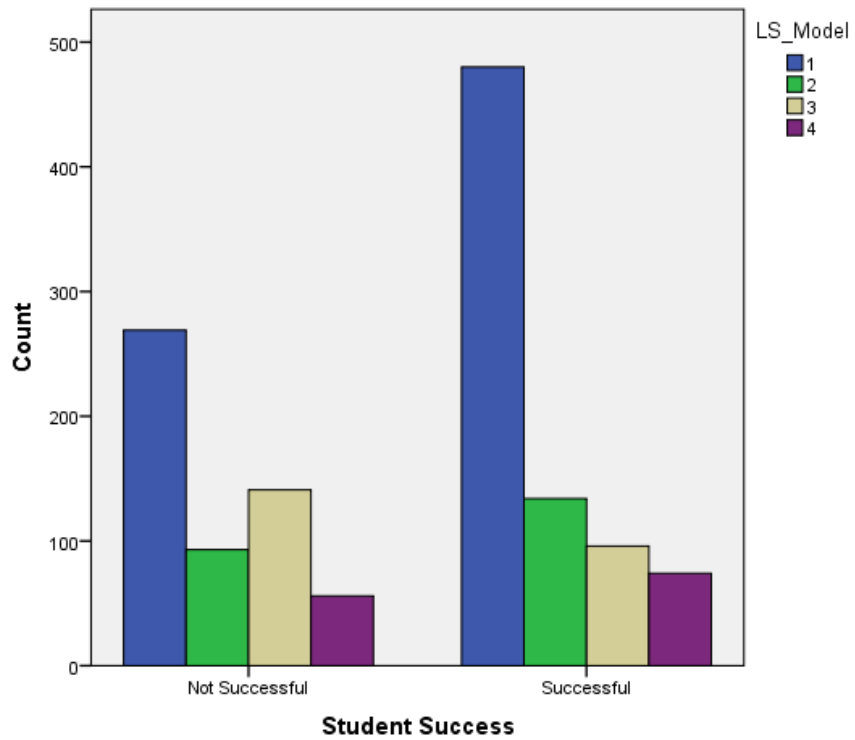


Figure 3 MATH 1530 students who scored 17 or 18 on the ACT Mathematics exam earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 7 shows the results of these analyses. The Holm’s sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (64.1%) vs. LS Model 3 (40.5%), between LS Model 2 (59.0%) vs. LS Model 3 (40.5%), and between LS Model 3 (40.5%) vs. LS Model 4 (56.9%), with models LS1, LS2, and LS4 being more successful than model LS3. Also, LS 1 Model (64.1%) vs. LS 4 Model (56.9%) and LS Model 1 (64.1%) vs. LS Model 2 (59.0%) were not statistically significant but did display a relatively large difference in student success with model LS1 being more successful than models LS2 and LS4.

Table 7

Pairwise Comparison Using the Holm’s Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	41.21*	<.001 (.008)	.20
LS2# vs. LS3	15.62*	<.001 (.010)	.19
LS3 vs. #LS4	9.01*	.003 (.013)	.16
LS1 vs. LS4	2.44	.118 (.017)	.05
LS1 vs. LS2	1.91	.167 (.025)	.04
LS2 vs. LS4	.15	.698 (.050)	.02

most successful model

**p* value ≤ alpha

Research Question 4

Is there a significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4?

Ho4: There is no significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of students who were successful and who were not successful in MATH 1630, Finite Mathematics, and scored 17 or 18 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found not to be significantly related, Pearson $\chi^2(3, N = 510) = 7.09$, $p=.069$, Cramer's $V = .18$. Therefore, the null hypothesis was retained.

Table 8 indicates the percentage of students in each grade group by learning support model. Figure 4 shows the count of the number of students in each grade group by learning support model.

Table 8

MATH 1630 Students Scoring 17 or 18 on the Mathematics Section of the ACT Exam Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	62.1	59.2	45.6	65.9
Not Successful	37.9	40.8	54.4	34.1
Total	100%	100%	100%	100%

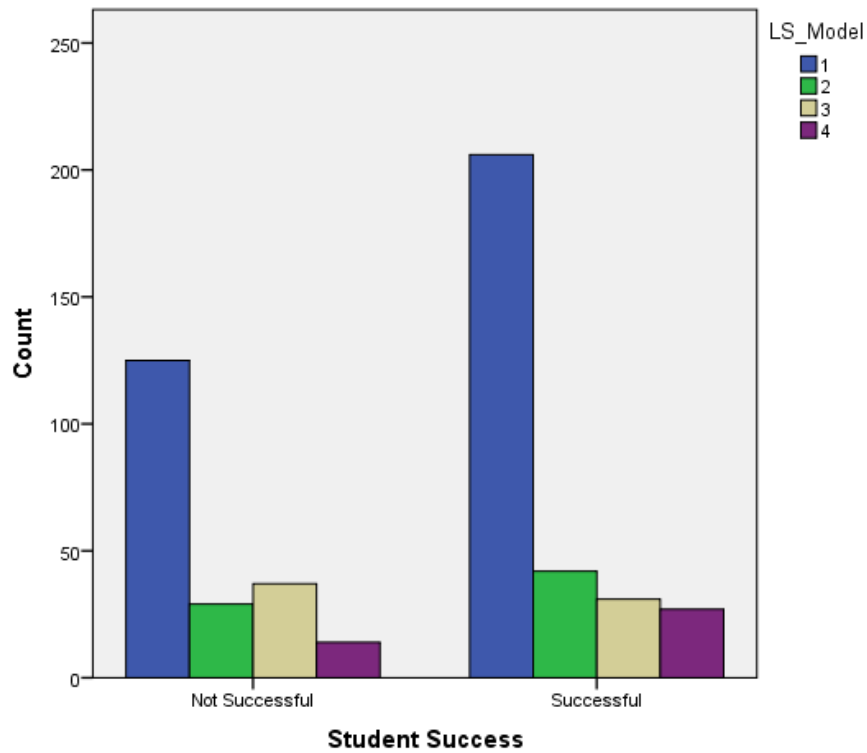


Figure 4 MATH 1630 students who scored 17 or 18 on the ACT Mathematics exam earning each final letter grade by LS Model

Research Question 5

Is there a significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4?

Ho5: There is no significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of students who were successful and who were not successful in MATH 1530, Probability and Statistics, and scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related, Pearson $\chi^2(3, N = 1181) = 13.85, p=.003$, Cramer's $V = .11$. Therefore, the null hypothesis was rejected.

Table 9 indicates the percentage of students in each grade group by learning support model. Figure 5 shows the count of the number of students in each grade group by learning support model.

Table 9

MATH 1530 Students Scoring 15 or 16 on the Mathematics Section of the ACT Exam Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	57.4	55.4	46.2	43.8
Not Successful	42.6	44.6	53.8	56.3
Total	100%	100%	100%	100%

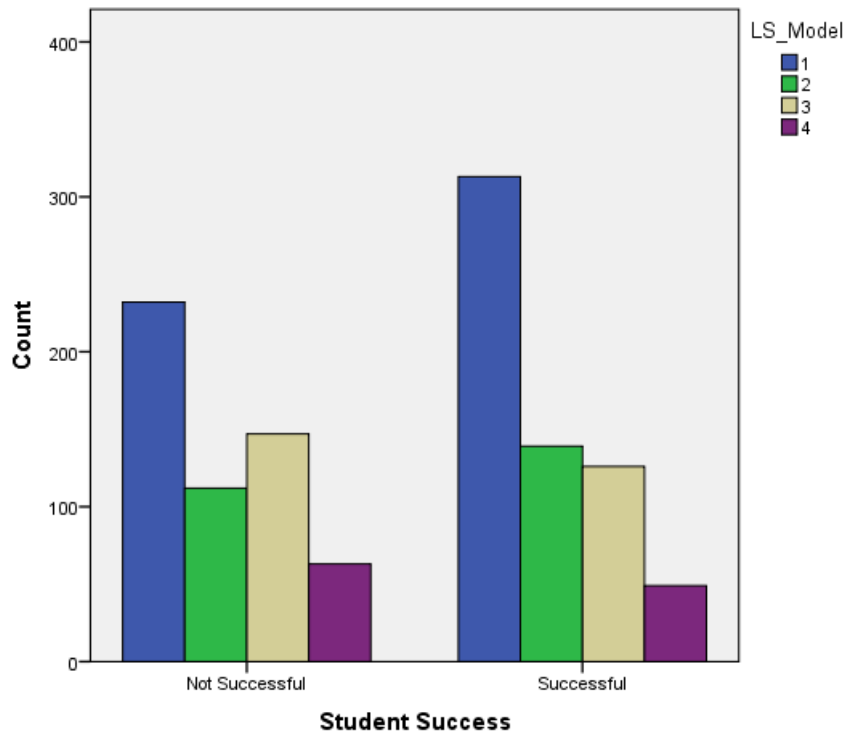


Figure 5 MATH 1530 students who scored 15 or 16 on the ACT Mathematics exam earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 10 shows the results of these analyses. The Holm’s sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (57.4%) vs. LS Model 3 (46.2%) and between LS Model 1 (57.4%) vs. LS Model 4 (43.8%), with model LS1 being more successful than models LS3 and LS4. Also, LS Model 2 (55.4) vs. LS Model 3 (46.2%) and LS Model 2 (55.4%) vs. LS Model 4 (43.8%) were not statistically significant but did display a relatively large difference in student success, with model LS2 being more successful than models LS3 and LS4.

Table 10

Pairwise Comparison Using the Holm’s Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	9.30*	.002 (.008)	.11
LS1# vs. LS4	7.03*	.008 (.010)	.10
LS2 vs. LS3	4.45	.035 (.013)	.09
LS2 vs. LS4	4.19	.041 (.017)	.11
LS1 vs. LS2	.30	.587 (.025)	.02
LS3 vs. LS4	.19	.667 (.050)	.02

most successful model

**p* value ≤ alpha

Research Question 6

Is there a significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4?

HO6: There is no significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of students who were successful and who were not successful in MATH 1630, Finite Mathematics, and scored 15 or 16 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found not to be significantly related, Pearson $\chi^2(3, N = 492) = 4.95$, $p = .176$, Cramer's $V = .10$. Therefore, the null hypothesis was retained.

Table 11 indicates the percentage of students in each grade group by learning support model. Figure 6 shows the count of the number of students in each grade group by learning support model.

Table 11

MATH 1630 Students Scoring 15 or 16 on the Mathematics Section of the ACT Exam Participating in Each LS Model by Grade Group

Success Category	LS Model			
	1	2	3	4
Successful	61.4	57.0	52.9	45.0
Not Successful	38.6	43.0	47.1	55.0
Total	100%	100%	100%	100%

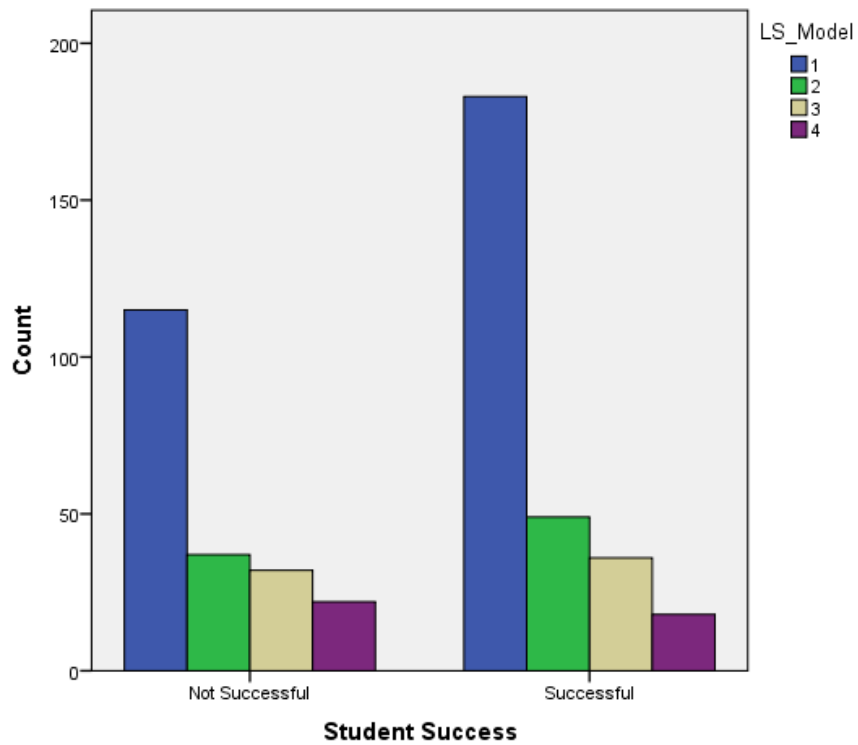


Figure 6 MATH 1630 students who scored 15 or 16 on the ACT Mathematics exam earning each final letter grade by LS Model

Research Question 7

Is there a significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4?

Ho7: There is no significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of students who were successful and who were not successful in MATH 1530, Probability and Statistics, and scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related, Pearson $\chi^2(3, N = 568) = 38.90, p < .001$, Cramer's $V = .26$. Therefore, the null hypothesis was rejected.

Table 12 indicates the percentage of students in each grade group by learning support model. Figure 7 shows the count of the number of students in each grade group by learning support model.

Table 12

MATH 1530 Students Scoring Below 15 on the Mathematics Section of the ACT Exam Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	61.0	60.8	31.1	28.6
Not Successful	39.0	39.2	68.9	71.4
Total	100%	100%	100%	100%

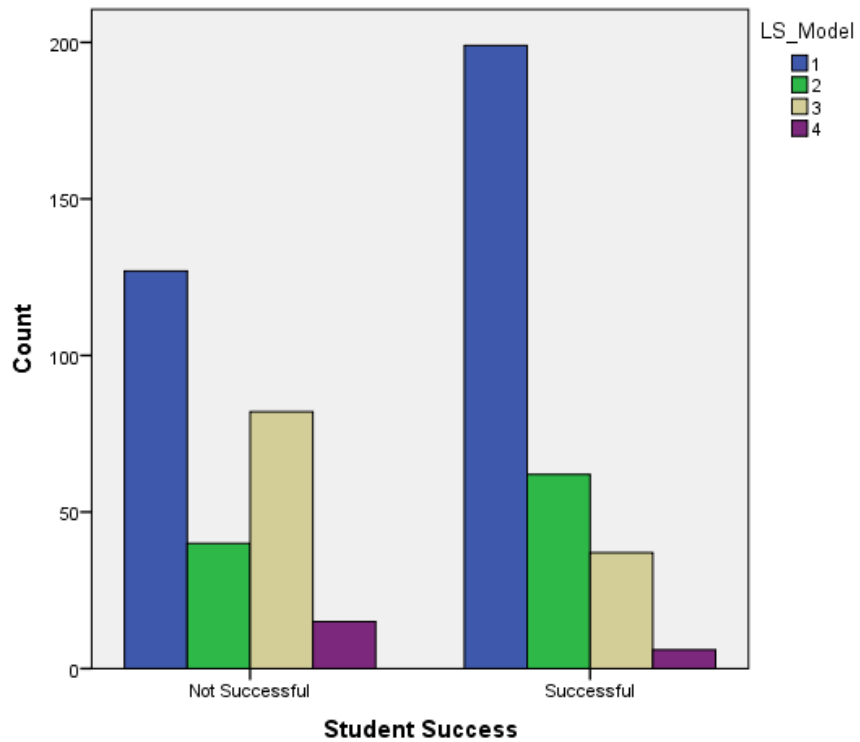


Figure 7 MATH 1530 students who scored below 15 on the ACT Mathematics exam earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 13 shows the results of these analyses. The Holm's sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (61.0%) vs. LS Model 3 (31.1%), between LS Model 2 (60.8%) vs. LS Model 3 (31.150.6%), between LS Model 1 (61.0%) vs. LS Model 4 (28.6%), and between LS Model 2 (60.8%) vs. LS Model 4 (28.6%), with model LS1 being more successful than models LS3 and LS4 and model LS2 being more successful than model LS3 and LS4.

Table 13

Pairwise Comparison Using the Holm's Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	31.40*	<.001 (.008)	.27
LS2# vs. LS3	19.58*	<.001 (.010)	.30
LS1# vs. LS4	8.61*	.003 (.013)	.16
LS2# vs. LS4	7.31*	.007 (.017)	.24
LS3 vs. LS4	.05	.817 (.025)	.02
LS1 vs. LS2	<.01	.963 (.050)	<.01

most successful model

**p* value ≤ alpha

Research Question 8

Is there a significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4?

Ho8: There is no significant difference in the proportion of students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, among students who scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of students who were successful and who were not successful in MATH 1630, Finite Mathematics, and scored less than 15 on the mathematics section of the ACT exam (or the equivalent scores on the mathematics section of the SAT exam or the ACT Compass exam) varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found not to be significantly related, Pearson $\chi^2(3, N = 210) = 7.52$, $p=.057$, Cramer's $V = .19$. Therefore, the null hypothesis was retained. Although the null hypothesis was retained, there is a substantive difference in the success rates of students participating models LS1 and LS2 (64.8% and 66.7%, respectively) and the success rates of students participating models LS3 and LS4 (40.6% and 50.0%, respectively)

Table 14 indicates the percentage of students in each grade group by learning support model. Figure 8 shows the count of the number of students in each grade group by learning support model.

Table 14

MATH 1630 Students Scoring Below 15 on the Mathematics Section of the ACT Exam Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	64.8	66.7	40.6	50.0
Not Successful	35.2	33.3	59.4	50.0
Total	100%	100%	100%	100%

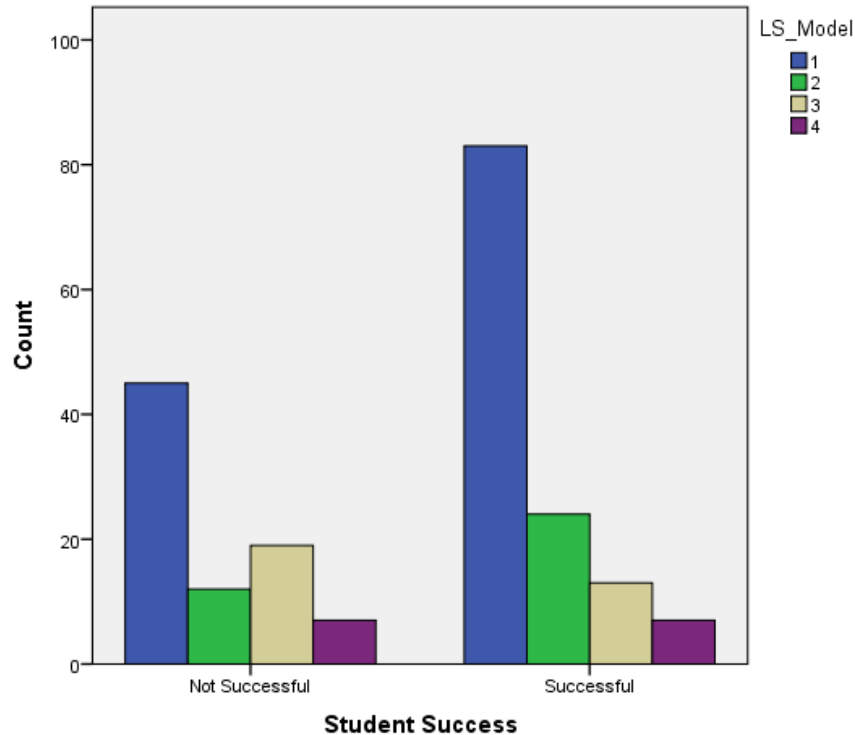


Figure 8 MATH 1630 students who scored below 15 on the ACT Mathematics exam earning each final letter grade by LS Model

Research Question 9

Is there a significant difference in the proportion of traditional age students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, or LS4?

Ho9: There is no significant difference in the proportion of traditional age students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of traditional age students who were successful and who were not successful in MATH 1530,

Probability and Statistics, varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related, Pearson $\chi^2(3, N = 2,381) = 27.40, p < .001$, Cramer's $V = .11$. Therefore, the null hypothesis was rejected.

Table 15 indicates the percentage of students in each grade group by learning support model. Figure 9 shows the count of the number of students in each grade group by learning support model.

Table 15

Traditional Age MATH 1530 Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	56.5	53.9	43.0	49.0
Not Successful	43.5	46.1	57.0	51.0
Total	100%	100%	100%	100%

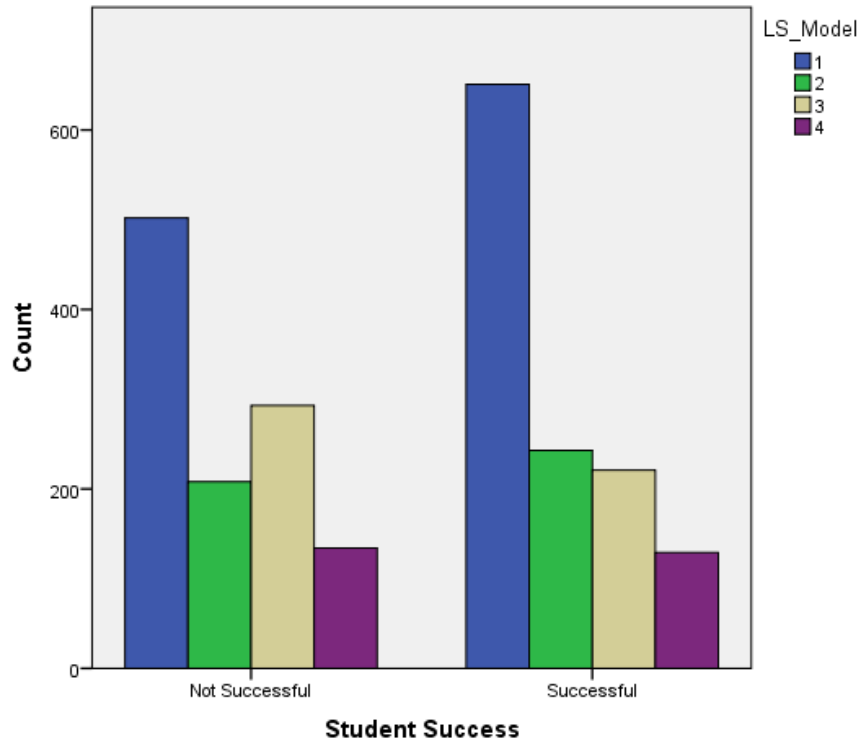


Figure 9 Traditional age MATH 1530 students earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 16 shows the results of these analyses. The Holm's sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (56.5%) vs. LS Model 3 (43.0%) and between LS Model 2 (53.9%) vs. LS Model 3 (43.0%), with models LS1 and LS2 being more successful than model LS3. Also, LS 1 Model (56.5%) vs. LS Model 4 (49.0%) was not statistically significant but did display a relatively large difference in student success, with model LS1 being more successful than model LS4.

Table 16

Pairwise Comparison Using the Holm's Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	25.84*	<.001 (.008)	.13
LS2# vs. LS3	11.40*	.001 (.010)	.11
LS1 vs. LS4	4.76	.029 (.013)	.06
LS3 vs. LS4	2.58	.109 (.017)	.06
LS2 vs. LS4	1.55	.213 (.025)	.05
LS1 vs. LS2	.88	.349 (.050)	.02

most successful model

**p* value \leq alpha

Research Question 10

Is there a significant difference in the proportion of nontraditional age students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, or LS3?

Ho10: There is no significant difference in the proportion of nontraditional age students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, or LS3.

A two-way contingency table analysis was used to evaluate whether the proportion of nontraditional age students who were successful and who were not successful in MATH 1530, Probability and Statistics, varied depending on the learning support model used for remediation.

The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, or LS3). Learning Support Model 4 was not included in this analysis because it has not been in use long enough for there to be students of nontraditional age who participated in the model. Student success and learning support model were found to be significantly related, Pearson $\chi^2(2, N = 711) = 67.76, p < .001$, Cramer's $V = .31$. Therefore, the null hypothesis was rejected.

Table 17 indicates the percentage of students in each grade group by learning support model. Figure 10 shows the count of the number of students in each grade group by learning support model.

Table 17

Nontraditional Age MATH 1530 Students Participating in Each LS Model by Student Success

Student Success	LS Model		
	1	2	3
Successful	73.0	71.3	33.0
Not Successful	27.0	28.7	67.0
Total	100%	100%	100%

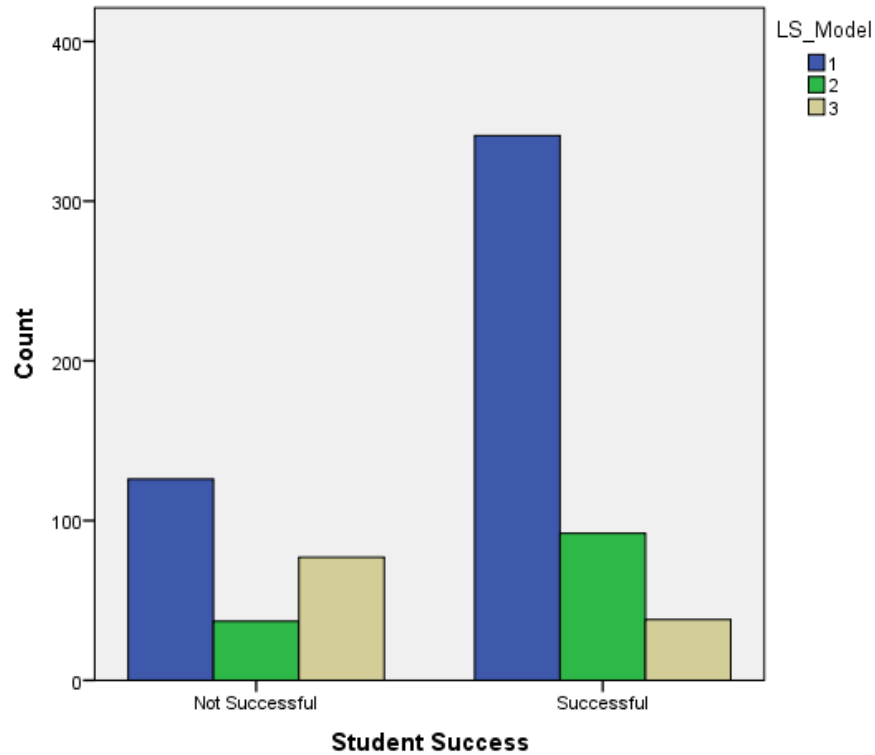


Figure 10 Nontraditional age MATH 1530 students earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 18 shows the results of these analyses. The Holm’s sequential Bonferroni method was used to control the Type I error at the .05 level across the three comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (73.0%) vs. LS Model 3 (33.0%) and between LS Model 2 (71.3%) vs. LS Model 3 (33.0%), with models LS1 and LS2 being more successful than model LS3.

Table 18

Pairwise Comparison Using the Holm's Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	64.92*	<.001 (.017)	.33
LS2# vs. LS3	35.78*	<.001 (.025)	.38
LS1 vs. LS2	.15	.701 (.050)	.02

most successful model

**p* value \leq alpha

Research Question 11

Is there a significant difference in the proportion of traditional age students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, or LS4?

Ho11: There is no significant difference in the proportion of traditional age students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of traditional age students who were successful and who were not successful in MATH 1630, Finite Mathematics, varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found not to be significantly

related, Pearson $\chi^2(3, N = 965) = 5.02, p=.170$, Cramer's $V = .07$. Therefore, the null hypothesis was retained.

Table 19 indicates the percentage of students in each grade group by learning support model. Figure 11 shows the count of the number of students in each grade group by learning support model.

Table 19

Traditional Age MATH 1630 Students Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	58.3	57.9	48.3	54.7
Not Successful	41.7	42.1	51.7	45.3
Total	100%	100%	100%	100%

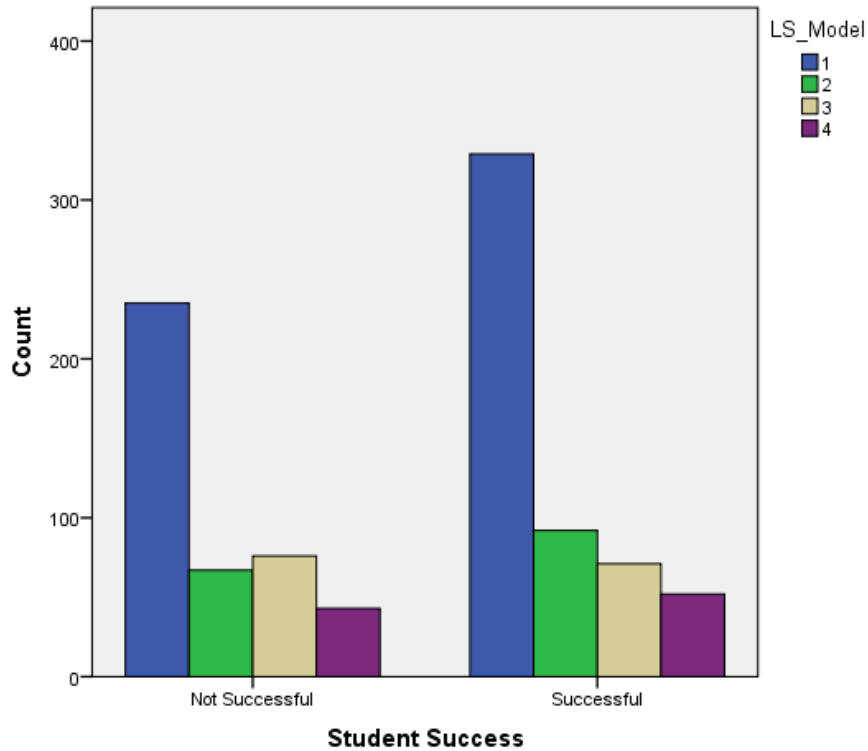


Figure 11 Traditional age MATH 1630 students earning each final letter grade by LS Model

Research Question 12

Is there a significant difference in the proportion of nontraditional age students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, or LS3?

Ho12: There is no significant difference in the proportion of nontraditional age students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, or LS3.

A two-way contingency table analysis was used to evaluate whether the proportion of nontraditional age students who were successful and who were not successful in MATH 1630,

Finite Mathematics, varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, or LS3). Learning Support Model 4 was not included in this analysis because it has not been in use long enough for there to be students of nontraditional age who participated in the model. Student success and learning support model were found to be significantly related, Pearson $\chi^2(2, N = 247) = 8.94, p=.011$, Cramer's $V = .19$. Therefore, the null hypothesis was rejected.

Table 20 indicates the percentage of students in each grade group by learning support model. Figure 12 shows the count of the number of students in each grade group by learning support model.

Table 20

Nontraditional Age MATH 1630 Students Participating in Each LS Model by Student Success

Student Success	LS Model		
	1	2	3
Successful	74.0	67.6	42.9
Not Successful	26.0	32.4	57.1
Total	100%	100%	100%

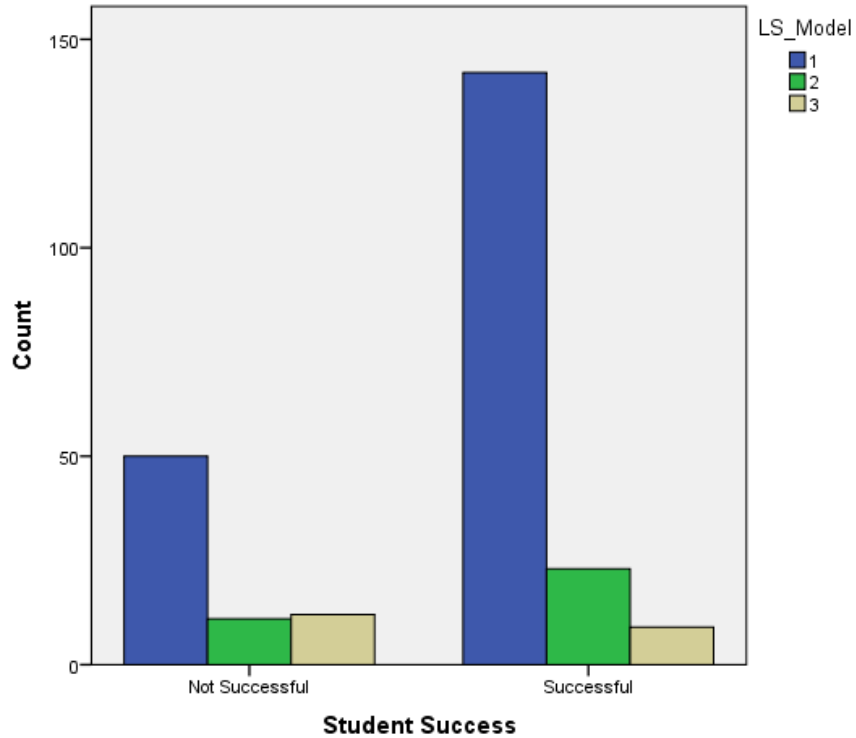


Figure 12 Nontraditional age MATH 1630 students earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 21 shows the results of these analyses. The Holm’s sequential Bonferroni method was used to control the Type I error at the .05 level across the three comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (74.0%) vs. LS Model 3 (42.9%), with model LS1 being more successful than model LS3. Also, LS Model 2(67.6%) vs. LS 3 Model (42.9%) was not statistically significant but did display a relatively large difference in student success, with model LS2 being more successful than model LS3.

Table 21

Pairwise Comparison Using the Holm's Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	8.87*	.003 (.017)	.20
LS2 vs. LS3	3.28	.070 (.025)	.24
LS1 vs. LS2	.58	.445 (.050)	.05

most successful model

**p* value \leq alpha*Research Question 13*

Is there a significant difference in the proportion of full-time students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, or LS4?

Ho13: There is no significant difference in the proportion of full-time students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of full-time students who were successful and who were not successful in MATH 1530, Probability and Statistics, varied depending on the learning support model used for remediation. The two variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related,

Pearson $\chi^2(3, N = 2,110) = 59.12, p < .001$, Cramer's $V = .17$. Therefore, the null hypothesis was rejected.

Table 22 indicates the percentage of students in each grade group by learning support model. Figure 13 shows the count of the number of students in each grade group by learning support model.

Table 22

Full-time MATH 1530 Students Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	60.1	55.3	40.4	46.0
Not Successful	39.9	44.7	59.6	54.0
Total	100%	100%	100%	100%

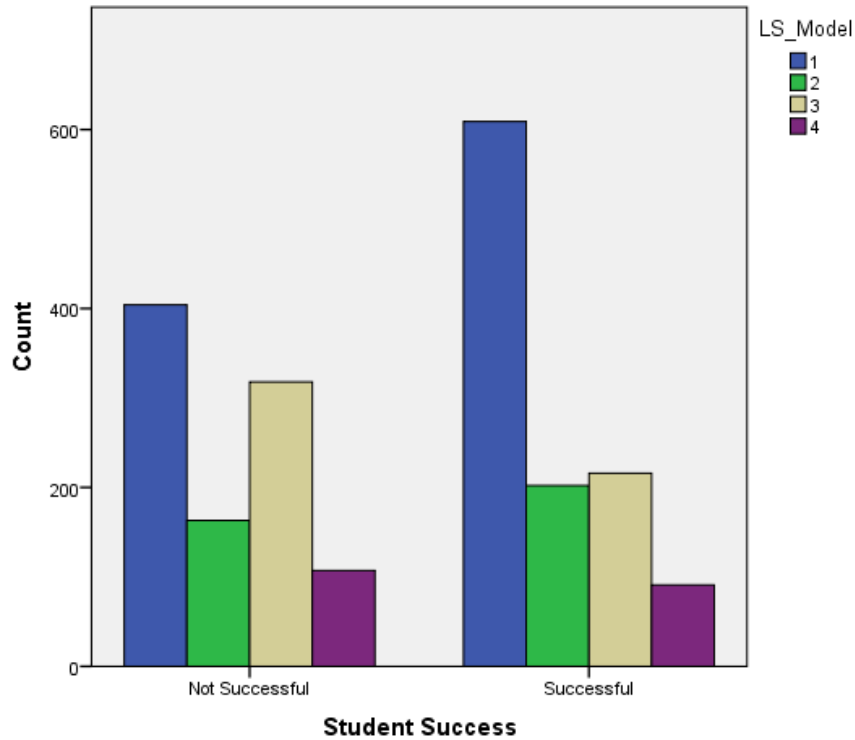


Figure 13 Full-time MATH 1530 students earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 23 shows the results of these analyses. The Holm's sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (60.1%) vs. LS Model 3 (40.4%), between LS Model 2 (55.3%) vs. LS Model 3 (40.4%) and between LS Model 1 (60.1%) vs. LS Model 4 (46.0%), with model LS1 being more successful than models LS3 and LS4 and model LS2 being more successful than model LS3. Also, LS 2 Model (55.3%) vs. LS 4 Model (46.0%) was not statistically significant but did display a relatively large difference in student success, with model LS2 being more successful than model LS4.

Table 23

Pairwise Comparison Using the Holm's Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	54.35*	<.001 (.008)	.19
LS2# vs. LS3	19.33*	<.001 (.010)	.15
LS1# vs. LS4	13.61*	<.001 (.013)	.11
LS2 vs. LS4	4.53	.033 (.017)	.06
LS1 vs. LS2	2.53	.112 (.025)	.04
LS3 vs. LS4	1.80	.180 (.050)	.05

most successful model

**p* value \leq alpha*Research Question 14*

Is there a significant difference in the proportion of part-time students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, or LS4?

Ho14: There is no significant difference in the proportion of part-time students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1530, Probability and Statistics, and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of part-time students who were successful and who were not successful in MATH 1530, Probability and Statistics, varied depending on the learning support model used for remediation. The two

variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related, Pearson $\chi^2(3, N = 982) = 11.22, p=.011$, Cramer's $V = .11$. Therefore, the null hypothesis was rejected.

Table 24 indicates the percentage of students in each grade group by learning support model. Figure 14 shows the count of the number of students in each grade group by learning support model.

Table 24

Part-time MATH 1530 Students Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	63.1	61.9	45.3	58.5
Not Successful	36.9	38.1	54.7	41.5
Total	100%	100%	100%	100%

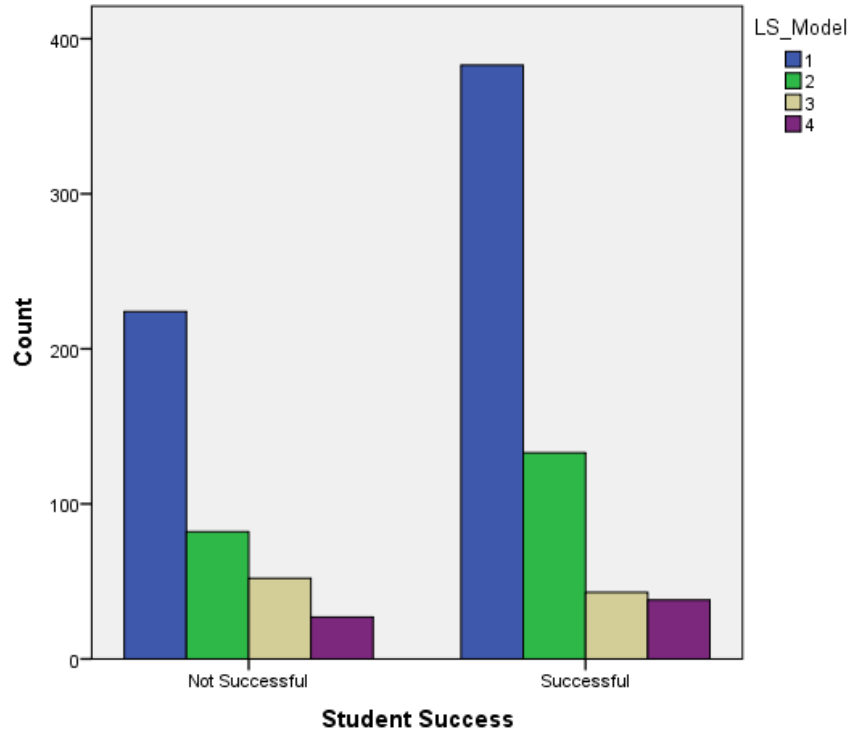


Figure 14 Part-time MATH 1530 students earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 25 shows the results of these analyses. The Holm's sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (63.1%) vs. LS Model 3 (45.3%) and between LS Model 2 (61.9%) vs. LS Model 3 (45.3%), with models LS1 and LS2 being more successful than model LS3. Also, LS Model 3 (45.3%) vs. LS Model 4 (58.5%) was not statistically significant but did display a relatively large difference in student success, with model LS4 being more successful than model LS3.

Table 25

Pairwise Comparison Using the Holm's Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	10.95*	.001 (.008)	.13
LS2# vs. LS3	7.40*	.007 (.010)	.15
LS3 vs. LS4	2.69	.101 (.013)	.13
LS1 vs. LS4	.54	.463 (.017)	.03
LS2 vs. LS4	.24	.622 (.025)	.03
LS1 vs. LS2	.10	.747 (.050)	.01

most successful model

**p* value \leq alpha*Research Question 15*

Is there a significant difference in the proportion of full-time students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, or LS4?

Ho15: There is no significant difference in the proportion of full-time students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of full-time students who were successful and who were not successful in MATH 1630, Finite Mathematics, varied depending on the learning support model used for remediation. The two

variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found to be significantly related, Pearson $\chi^2(3, N = 848) = 16.78, p=.001$, Cramer's $V = .14$. Therefore, the null hypothesis was rejected.

Table 26 indicates the percentage of students in each grade group by learning support model. Figure 15 shows the count of the number of students in each grade group by learning support model.

Table 26

Part-time MATH 1630 Students Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	65.8	59.1	48.6	52.4
Not Successful	34.2	40.9	51.4	47.6
Total	100%	100%	100%	100%

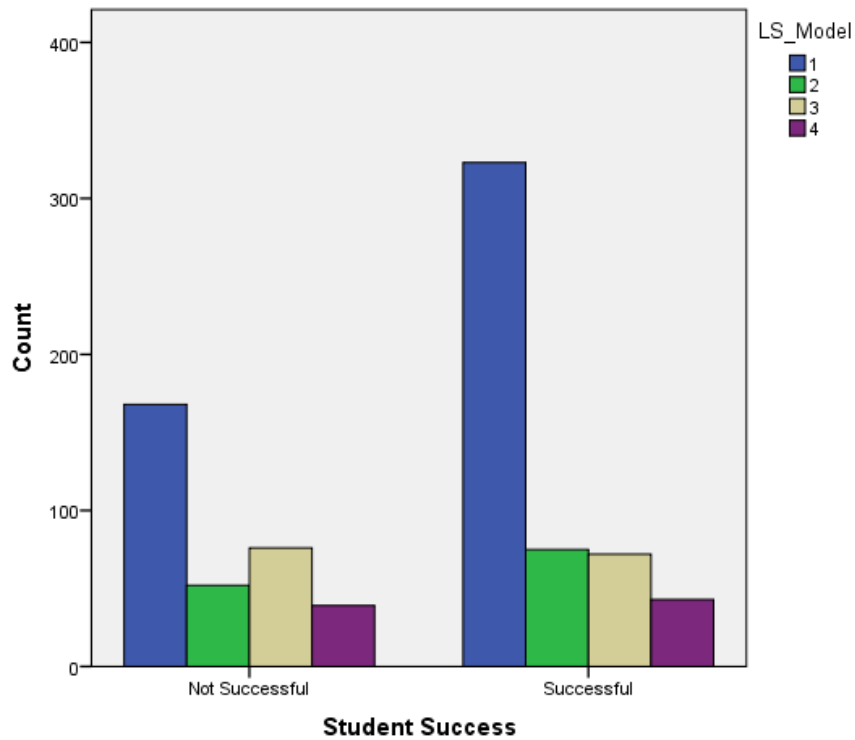


Figure 15 Full-time MATH 1630 students earning each final letter grade by LS Model

Follow-up pairwise comparisons were performed to evaluate specific differences among proportions of students who participated in each LS Model. Table 27 shows the results of these analyses. The Holm’s sequential Bonferroni method was used to control the Type I error at the .05 level across the six comparisons conducted. In general, student success was significantly different between those participating in LS Model 1 (65.8%) vs. LS Model 3 (48.6%), with model LS1 being more successful than model LS3. Also, LS Model 1 (65.8%) vs. LS Model 4 (52.4%) and LS Model 2 (59.1%) vs. LS Model 3 (48.6%) were not statistically significant but did display a relatively large difference in student success, with model LS1 being more successful than model LS4, and model LS2 more successful than model LS3.

Table 27

Pairwise Comparison Using the Holm's Sequential Bonferroni Method

Comparison	Pearson Chi-square	<i>p</i> value (alpha)	Cramer's <i>V</i>
LS1# vs. LS3	14.15*	<.001 (.008)	.15
LS1 vs. LS4	5.42	.020 (.010)	.10
LS2 vs. LS3	2.98	.085 (.013)	.10
LS1 vs. LS2	1.99	.158 (.017)	.06
LS2 vs. LS4	.89	.346 (.025)	.07
LS3 vs. LS4	.30	.582 (.050)	.04

most successful model

**p* value \leq alpha*Research Question 16*

Is there a significant difference in the proportion of part-time students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, or LS4?

Ho16: There is no significant difference in the proportion of part-time students who were successful (a final course grade of A, B, or C) and who were not successful (a final course grade of D or F) in MATH 1630, Finite Mathematics, and participated in learning support models LS1, LS2, LS3, or LS4.

A two-way contingency table analysis was used to evaluate whether the proportion of part-time students who were successful and who were not successful in MATH 1630, Finite Mathematics, varied depending on the learning support model used for remediation. The two

variables were grade group (successful or not successful) and learning support model (LS1, LS2, LS3, or LS4). Student success and learning support model were found not to be significantly related, Pearson $\chi^2(3, N = 364) = 3.56, p=.313$, Cramer's $V = .10$. Therefore, the null hypothesis was retained.

Table 28 indicates the percentage of students in each grade group by learning support model. Figure 16 shows the count of the number of students in each grade group by learning support model.

Table 28

Part-time MATH 1630 Students Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
Successful	55.8	60.6	40.0	69.2
Not Successful	44.2	39.4	60.0	30.8
Total	100%	100%	100%	100%

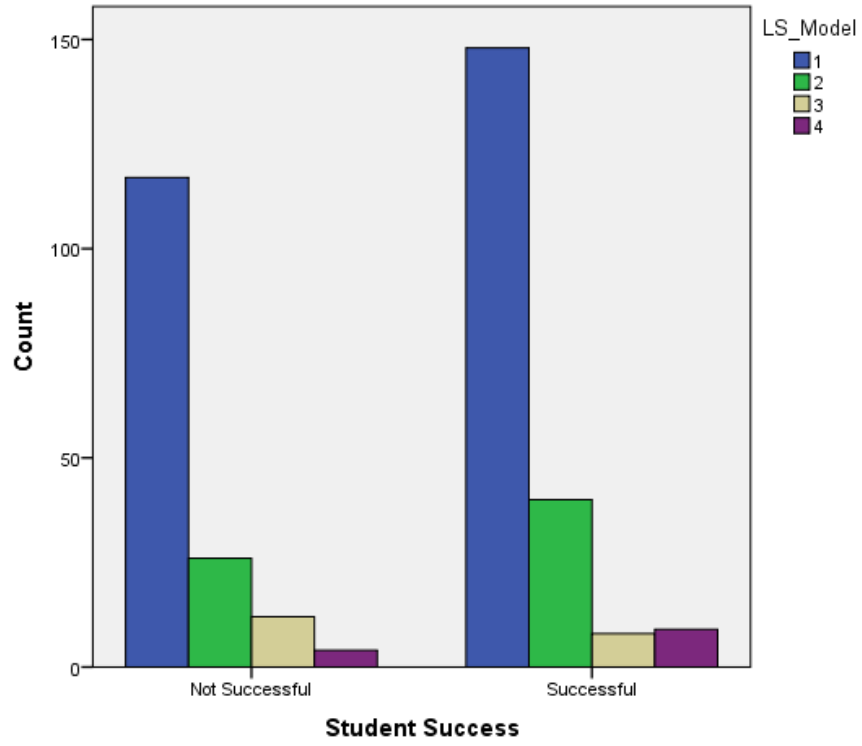


Figure 16 Part-time MATH 1630 students earning each final letter grade by LS Model

CHAPTER 5

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

Summary of the Findings

A review of literature was conducted on the history and methodologies of remedial education in higher education. The need for remediation in higher education is a major problem, with the need being more pronounced at the community college level where nearly 75% of community college students required remedial coursework when entering college (Mangan, 2013b). In Tennessee most students placed into remedial coursework had deficiencies in mathematics. In 2015 57.3% of Tennessee high school students who took the ACT exam scored below the TBR established cutoff score as compared to 46.7% scoring below the TBR established cutoff score in English and 49.6% scoring below the TBR established cutoff score in reading (ACT profile report – state: Graduating Class 2015 Tennessee, 2015). For many years remediation within the community college system in Tennessee consisted of prerequisite coursework that had to be successfully completed before a student was allowed to attempt college level coursework in the subject area in which remediation was required. While small changes were frequent within the institutions' approaches to remediation, the practice of remediation did not experience significant modification until the influence of Complete College America (CCA) began to emerge after the organization was established in 2009 (Complete College America, n.d.).

The CCA organization adopted five principles upon which the organization's mission was and currently is founded. These principles, called Game Changers, include the mindset that corequisite learning support must replace prerequisite remediation models in order for the number of American citizens with postsecondary credentials to significantly increase (Game

changers, n.d.). It is the belief of CCA's leadership that remediation is a barrier that negatively impacts college retention and graduation, with only 9.5% of students pursuing a 2-year degree with remediation requirements complete their degree requirements in 3 years (Complete College America, n.d.). While there are other factors that could likely contribute to this dismal statistic, CCA promotes the belief that students facing multiple semesters of remediation courses often become discouraged and do not complete their degree requirements (Remediation, 2012).

Tennessee has worked since the inception of the Complete College Tennessee Act of 2010 (Complete College Tennessee Act of 2010, 2010) to reduce the number of courses and semester hours of remediation an institution can require a student to register for from nine prerequisite semester hours to five in 2013; then from five prerequisite semester hours to three corequisite hours in 2015. These substantive changes have been justified by multiple studies indicating the increased student success of corequisite remediation models (The Results are in, 2015). However, proponents of prerequisite remediation have countered by indicating that the potential success of corequisite remediation was based on misinterpretations and misapplications of data (Goudas & Boylan, 2012). Chapter 2 presented information that was relevant to this study in further depth and detail.

The problem addressed in this study was that the actual impacts of these changes in remediation at Walters State Community College were not known. This study was designed to determine these impacts on the levels of student success for those who were required to participate in mathematics remediation based on their performance on the mathematics sections of the ACT, SAT, and ACT Compass exams. The two college level mathematics courses chosen for this study were MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics. These courses were selected because the majority of students in degree seeking

programs were and are currently required to complete one of the two, and because these courses were and are currently two of the three that current corequisite remediation courses were and are currently paired with. Student grades in these two courses were sorted into two groups; those that were successful and those that were not successful. Grades of A, B, or C were considered successful because of course transferability to 4-year institutions and because many Associate of Applied Science degree programs have specific acceptance criteria requiring minimum grades of C in general education coursework for consideration for admission into the programs.

Data for this study were drawn from the student database at Walters State Community College. Beginning with the fall 2011 semester and continuing through the spring 2016 semester, students who had taken either MATH 1530, Probability and Statistics, or MATH 1630, Finite Mathematics were selected for consideration for this study. The data set also contained information that allowed each remaining student record to be categorized by the type of remediation method they had participated in. Four remediation methods were used during the selected time frame.

Learning Support Model 1 (LS1) was used during the fall semester 2011 through the summer semester 2013. This model consisted of three courses, each comprising three semester hours. This was a prerequisite model with students placed into the course sequence depending on their ACT scores. Learning Support Model 2 (LS2) was a five course sequence, with each course consisting of one credit hour. This was also a prerequisite model used from the fall semester 2013 through the summer semester 2015. Learning Support Model 3 (LS3) consists of a single 3-hour corequisite course introduced during the fall semester 2015 and is still in use. Learning Support Model 4 (LS4) is a course taught within area high schools. Students successfully

completing the five modules were considered having completed all mathematics remediation requirements. These students began entering the college during the fall semester of 2014, and the model is still in use.

The general populations of MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, were studied to determine the overall statistical significance of the impacts of the various learning support models relevant to student success. Afterward, each population was further divided into groups based on ACT scores, student age, and attendance status to determine if the various learning support models influenced student success in each of these student populations. These combinations yielded 16 research questions. Chi-square analyses were used to study each research question. Each question that yielded statistical significance was further evaluated using pairwise comparisons where the Holm's sequential Bonferroni method was applied to control for Type I error at the .05 level of significance.

Research questions 1 and 2 addressed the differences in success rates among the students in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics. For both courses the highest levels of success came from Learning Support Model 1. The lowest levels of success for both courses came from Learning Support Model 3. All four comparisons between student success in Learning Support Models 1 (61.2%) and 2 (57.8%) vs. Learning Support Models 3 (41.2%) and 4 (49.0%) were found to be statistically significant, with Learning Support Models 1 and 2 showing higher student success rates. The difference between student success in Learning Support Model 1 (62.3%) vs. Learning Support Model 3 (47.6%) proved to be the only significant pairing that yielded statistical significance for MATH 1630, Finite Mathematics. The differences in statistical significance between research questions 1 and 2 indicate that the current corequisite model and the high school SAILS model were not as

effective in contributing to student success in MATH 1530, Probability and Statistics, as they were for MATH 1630, Finite Mathematics. The fewer statistically significant pairings in research question 2 indicate that the current designs of Learning Support Models 3 and 4 are not as successful in contributing to the successful completion of MATH 1530, Probability and Statistics. However, Learning Support Models 3 and 4 have a greater potential of contributing to the successful completion of MATH 1630, Finite Mathematics. Tables 2 and 4 contain the student success percentages for research questions 1 and 2.

Research questions 3 and 4 addressed the differences in success rates among the students in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, who had scored 17 or 18 on the mathematics section of the ACT exam (or equivalent scores on the math sections of the SAT exam or the ACT Compass exam). Research question 3 addressed student success rates in MATH 1530, Probability and Statistics, and the results of the Chi-square analysis was that a statistically significant difference existed in student success between the four learning support models. The pairwise comparisons follow-up indicated statistically significant differences between Learning Support Model 1 (64.1%) vs. Learning Support Model 3 (40.5%), Learning Support Model 2 (59.0%) vs. Learning Support Model 3 (40.5%), and Learning Support Model 3 (40.5%) vs. Learning Support Model 4 (56.9%), with Learning Support Model 3 proving to be significantly less successful than the other three models. Given this, it is concluded that the current design of Learning Support Model 3 was not as successful in contributing to the successful completion of MATH 1530, Probability and Statistics.

Research question 4 addressed student success rates in MATH 1630, Finite Mathematics, and there was no statistically significant difference in student success among the four learning support models (p value = .069). Though not statistically significant, a comparison of the success

rates of the four models found the student success rate of Learning Support Model 3 between 13.6 and 20.3 percentage points lower than the success rates of the other learning support models. It was atypical that Learning Support Model 4 had the highest student success rate of the four models at 65.9%, as this model produced the highest success rate related to only one other research question, that being research question 16. Tables 6 and 8 contain the student success percentages for research questions 3 and 4.

Research questions 5 and 6 addressed the differences in success rates among the students in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, who had scored 15 or 16 on the mathematics section of the ACT exam (or equivalent scores on the math sections of the SAT exam or the ACT Compass exam). Research question 5 addressed student success rates in MATH 1530, Probability and Statistics, and the results of the Chi-square analysis were that a statistically significant difference existed in student success between the four learning support models. The pairwise comparisons follow-up indicated significant differences between Learning Support Model 1 (57.4%) vs. Learning Support Model 3 (46.2%) and Learning Support Model 1 (57.4%) vs. Learning Support Model 4 (43.8%), with Learning Support Model 1 yielding a higher student success percentage than Learning Support Models 3 and 4. Though not statistically significant, the differences in student success rates between Learning Support Model 2 (55.4%) vs. Learning Support Model 3 (46.2%) and Learning Support Model 2 (55.4%) vs. Learning Support Model 4 (43.8%) were noteworthy, with Learning Support Model 2 yielding a higher student success percentage than Learning Support Models 3 and 4. These results indicate that the current designs of Learning Support Models 3 and 4 are not as successful in contributing to the successful completion of MATH 1530, Probability and Statistics.

Research question 6 addressed student success rates in MATH 1630, Finite Mathematics, and there was no statistically significant difference in student success among the four learning support models (p value = .176). Though not statistically significant, a comparison of the success rates of the four models found the student success rate of Learning Support Model 4 between 7.9 and 16.4 percentage points lower than the success rates of the other learning support models. Tables 9 and 11 contain the student success percentages for research questions 5 and 6.

Research questions 7 and 8 addressed the differences in success rates among the students in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, who had scored less than 15 on the mathematics section of the ACT exam (or equivalent scores on the math sections of the SAT exam or the ACT Compass exam). Research question 7 addressed student success rates in MATH 1530, Probability and Statistics, and the results of the Chi-square analysis were that a statistically significant difference existed in student success between the four learning support models. The pairwise comparisons follow-up indicated significant differences between Learning Support Model 1 (61.0%) vs. Learning Support Model 3 (31.1%), Learning Support Model 2 (60.8%) vs. Learning Support Model 3 (31.1%), Learning Support Model 1 (61.4%) vs. Learning Support Model 4 (28.6%), and Learning Support Model 2 (68.8%) vs. Learning Support Model 4 (28.6%), with Learning Support Models 1 and 2 being more successful than Learning Support Models 3 and 4. These results indicate that the current designs of Learning Support Models 3 and 4 are not as successful in contributing to the successful completion of MATH 1530, Probability and Statistics.

Research question 8 addressed student success rates in MATH 1630, Finite Mathematics. There was no statistically significant difference in student success among the four learning support models (p value = .057). Though not significant, student success between Learning

Support Models 1 (64.8%) and 2 (66.7%) vs. Learning Support Models 3 (40.6%) and 4 (50.0%) differed between 14.8 and 26.1 percentage points, with Learning Support Models 1 and 2 being more successful than Learning Support Models 3 and 4. Tables 12 and 14 contain the student success percentages for research questions 7 and 8.

In comparing student success percentages in MATH 1530, Probability and Statistics, across the learning support models between the three ACT score categories, it can be seen that, no matter the ACT score category, success rates in Learning Support Models 1 and 2 are similar. The success rates for Learning Support Model 3 were below 50% for all ACT score categories. The success rates of students participating in Learning Support Model 4 who scored below 17 on the ACT mathematics exam are similar to the success rates of students who participated in Learning Support Model 3 and whose ACT mathematics scores were below 17. The inconsistency of the Learning Support Model 4 students scoring 17 or 18 on the ACT mathematics exam cannot be explained with the data provided for this study. These comparisons show that, as ACT mathematics scores decline, Learning Support Models 1 and 2 consistently provide higher levels of student success than Learning Support Models 3 and 4 in MATH 1530, Probability and Statistics. Figure 17 shows the success percentages for each learning support model by ACT score category.

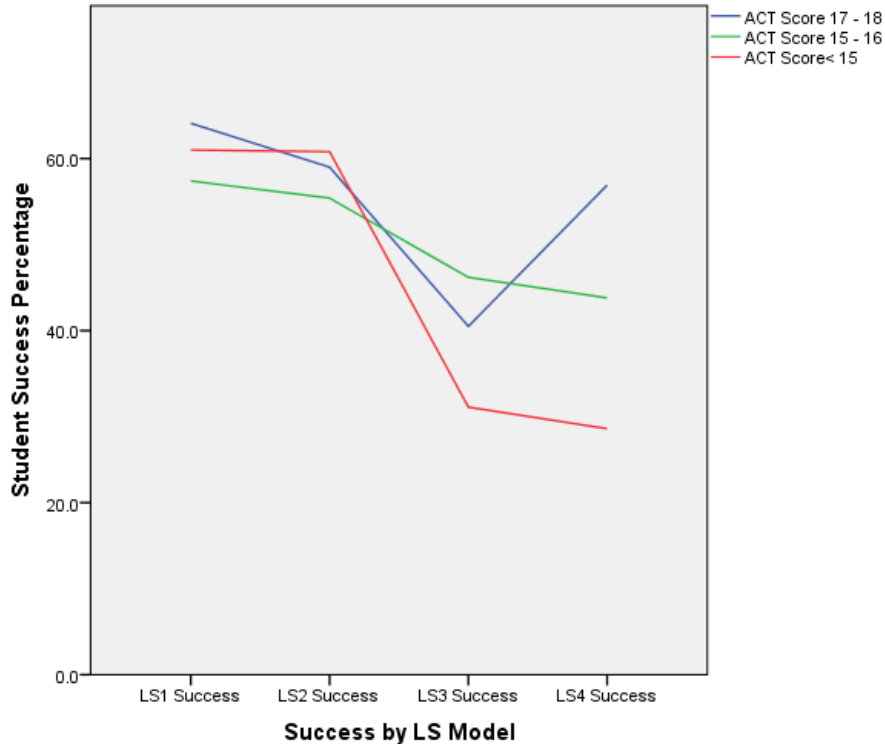


Figure 17 MATH 1530 student success percentages for each learning support model by ACT score category

In comparing student success percentages in MATH 1630, Finite Mathematics, across the learning support models between the three ACT score categories, it can be seen that, no matter the ACT score category, success rates in Learning Support Models 1 and 2 are similar.

Reviewing the graph found in Figure 18, the lowest success rate for Learning Support Models 1 and 2 was 57% for students participating in Learning Support Model 2 with ACT scores of 15 and 16. The highest success rate was 66.7%, also for students participating in Learning Support Model 2, but with ACT scores below 15. The success rates for Learning Support Model 3 were below 53% for all ACT score categories. The success rates of students participating in Learning Support Model 4 who scored below 17 on the ACT mathematics exam are similar to the success rates of students who participated in Learning Support Model 3 and whose ACT mathematics

scores were below 17. The inconsistency of the Learning Support Model 4 students scoring 17 or 18 on the ACT mathematics exam cannot be explained with the data provided for this study. It is noteworthy that the student success of students with ACT Mathematics scores below 15 in MATH 1630, Finite Mathematics is markedly higher than the success of students with ACT mathematics scores below 15 in MATH 1530, Probability and statistics. These comparisons show that, as ACT mathematics scores decline, Learning Support Models 1 and 2 consistently provide higher levels of student success than Learning Support Models 3 and 4 in MATH 1630, Finite Mathematics. The exception being students participating in Learning Support Model 4 with ACT scores of 17 and 18. Figure 18 shows the success percentages for each learning support model by ACT score category.

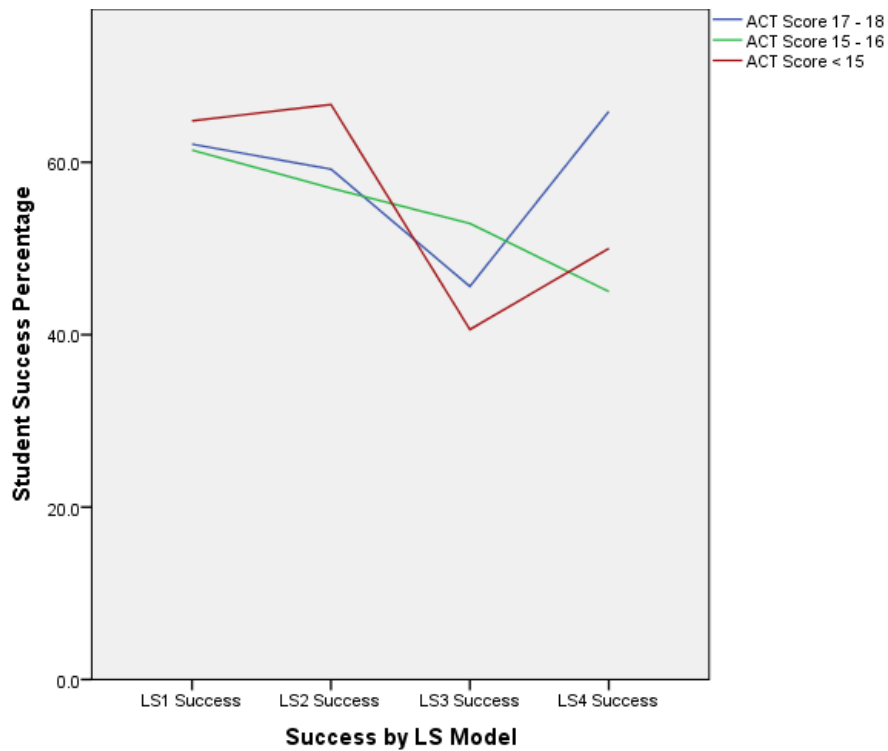


Figure 18 MATH 1630 student success percentages for each learning support model by ACT score category

Research questions 9, 10, 11, and 12 addressed the differences in success rates among traditional and nontraditional age students in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics. Students were considered to be traditional age if they were under the age of 25 and nontraditional age if they were 25 years of age and above.

Research question 9 addressed traditional age student success in MATH 1530, Probability and Statistics. A statistically significant difference in student success was found, with follow-up pairwise comparisons between Learning Support Model 1 (56.5%) vs. Learning Support Model 3 (43.0%) and Learning Support Model 2 (53.9%) vs. Learning Support Model 3 (43.0%), with Learning Support Models 1 and 2 having the highest rate of student success in both comparisons.

Research question 11 addressed traditional age student success in MATH 1630, Finite Mathematics. No statistically significant difference in student success was found. The largest difference in student success was between Learning Support Model 1 (58.3%) vs. Learning Support Model 3 (48.3%).

When comparing the success rates of traditional age students between the two courses, the results appeared similar, even though there was no statistical significance in research question 11's Chi-square evaluation results. It is noteworthy that Learning Support Models 1 and 2 produced the highest levels of student success, and the corequisite model produce the lowest levels of student success. The significance found in research question 9 and the similarity in trends in question indicate the current design for Learning Support Model 3 is less effective in preparing traditional students for success in both MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, than the other learning support models. Tables 15 and 19 contain the student success percentages for research questions 9 and 11.

Research questions 10 and 12 addressed nontraditional age student success in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics. The questions differ from the rest in the study in that Learning Support Model 4 is not included in either analysis. Learning Support Model 4 (SAILS Math) is offered exclusively to high school seniors who failed to meet the ACT score of 19. Because the program's first students entered college in the fall of 2014 not enough time had passed for the first students to have reached the age of 25. Also, SAILS Math scores expire after 2 years, meaning that the nontraditional student population will not factor into this learning support model.

Statistical significance was found in the Chi-square evaluation results for questions 10 and 12. Pairwise comparisons for research question 10 showed more statistical significance than for like comparisons for research question 10, with significant differences in student success found between Learning Support Model 1 (73.0%) vs. Learning Support Model 3 (33.0%) and Learning Support Model 2 (71.3%) vs. Learning Support Model 3 (33.0%). The pairwise comparisons for research question 12 found significance in student success in only the comparison between Learning Support Model 1 (74.0%) vs. Learning Support Model 3 (42.9%), though the comparison between Support Model 2 (67.6%) vs. Learning Support Model 3 (42.9%) was large, with the student success of learning Support Model 2 being 24.7 percentage points higher than the student success of Learning Support Model 3. Like the analyses involving research question 9 and 11, the analyses involving research questions 10 and 12 indicate that Learning Support Model 3 is less effective in preparing nontraditional students for success in both MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, than the other learning support models. Tables 17 and 20 contain the student success percentages for research questions 10 and 12.

Research questions 13, 14, 15, and 16 addressed the differences in success rates among full-time and part-time students in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics. Students were considered to be of full-time status if they were enrolled for a minimum of 12 semester hours, including the college level course being studied.

Research question 13 evaluated full-time student success in MATH 1530, Probability and Statistics. A statistically significant difference in student success was found, with follow-up pairwise comparisons showing statistical significance between Learning Support Model 1 (60.1%) vs. Learning Support Model 3 (40.4%), Learning Support Model 2 (55.3%) vs. Learning Support Model 3 (40.4%), and Learning Support Model 1 (60.1%) vs. Learning Support Model 4 (46.0%). Though not statistically significant, a difference in student success of 9.3 percentage points was found between Learning Support Model 2 vs. Learning Support Model 4, with Learning Support Model 2 being more successful. These results indicate that the current designs of Learning Support Models 3 and 4 are less effective in preparing full-time students for success in MATH 1530, Probability and Statistics.

Research question 15 addressed full-time student success in MATH 1630, Finite Mathematics. A statistically significant difference in student success was found, with follow-up pairwise comparisons showing a statistical significance between Learning Support Model 1 (65.8%) vs. Learning Support Model 3 (48.6%). Though not statistically significant, a difference in student success of 13.4 percentage points was found between Learning Support Model 1 vs. Learning Support Model 4 and 10.5 percentage points between Learning Support Model 2 vs. Learning Support Model 3, with Learning Support Models 1 and 2 being more successful in cases. These results indicate that the current designs of Learning Support Model 3 was less effective in preparing full-time students for success in MATH 1630, Finite Mathematics.

Research question 14 addressed part-time student success in MATH 1530, Probability and Statistics. A statistically significant difference in student success was found, with follow-up pairwise comparisons showing statistical significances between Learning Support Model 1 (63.1%) vs. Learning Support Model 3 (45.3%) and Learning Support Model 2 (61.9%) vs. Learning Support Model 3 (45.3%), with Learning Support Models 1 and 2 being more successful than Learning Support Model 3. Though not statistically significant, a difference in student success of 13.2 percentage points was found between Learning Support Model 3 vs. Learning Support Model 4, with Learning Support Model 4 being more successful than Learning Support Model 3.

Research question 16 addressed part-time student success in MATH 1630, Finite Mathematics. No statistically significant difference in student success was found in the initial Chi-square evaluation. Though not statistically significant a difference in student success of 15.8 percentage points was found between Learning Support Model 1 vs. Learning Support Model 3, and 20.6 percentage points between Learning Support Model 2 and Learning Support Model 3, with Learning Support Models 1 and 2 being more successful in both cases. There was an anomaly with the student success rate for Learning Support Model 4 (69.2%). The differences between the student success percentages of Learning Support Models 1 (55.8%), 2 (60.6%) and 3 (40.0%) vs. Learning Support Model 4 (69.2%) varied between 8.6 and 29.2 percentage points.

Table 29 displays the student success rates by learning support model for research questions 13, 14, 15, and 16. The statistical significance on research questions 13, 14, and 15, coupled with the data trend for the student success rates by learning support model for research question 16, indicate that the current design of Learning Support Model 16 is not as effective in

preparing students for success in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, as the previously used prerequisite models.

Table 29

MATH 1530 and MATH 1630 Full-time and Part-time Students Participating in Each LS Model by Student Success

Student Success	LS Model			
	1	2	3	4
MATH 1530 Full-time	60.1	55.3	40.4	46.0
MATH 1530 Part-time	63.1	61.9	45.3	58.5
MATH 1630 Full-time	65.8	59.1	48.6	52.4
MATH 1630 Part-time	55.8	60.6	40.0	69.2

Conclusion

Conclusions were drawn based on the analyses of the results of the 16 research questions evaluated in this study. They include:

1. The design of the current corequisite Learning Support Model 3 does not prepare students for success in MATH 1530, Probability and Statistics as well as the prerequisite Learning Support Models 1 and 2.
2. The design of the current corequisite Learning Support Model 3 is a more effective method for supporting students taking MATH 1630, Finite Mathematics, than for MATH 1530, Probability and Statistics. However, it is not as effective as the prerequisite Learning Support Models 1 and 2.

3. Students who score below 15 on the mathematics section of the ACT exam (or equivalent scores from other exams) and participate in Learning Support Model 3 are less successful in MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, than students with like ACT mathematics scores who participated in the prerequisite Learning Support Models 1 and 2.
4. In its current design Learning Support Model 4 (SAILS Math) is effective for students who scored either a 17 or 18 on the mathematics section of the ACT exam but is less effective if their score is below 17.
5. Nontraditional age students are less successful when participating in the corequisite Learning Support Model 3 than in the prerequisite Learning Support Models 1 and 2.
6. Between full-time students and part-time students, students participating in Learning Support Model 3 experienced the lowest success rates, regardless of enrollment status.

Recommendations for Practice

The findings of this study suggest that the corequisite remediation model at Walters State Community College in its current form requires modification. The current model shows promise as a viable support course for MATH 1630, Finite Mathematics, but improvements should be made in order to increase success rates to the Learning Support Model 1 and 2 levels. It is evident that improvements to the corequisite model are required in order to provide a viable support course for MATH 1530, Probability and Statistics. A reason for the difference in student success between MATH 1530, Probability and Statistics, and MATH 1630, Finite Mathematics, could lie in the fact that remedial mathematics courses were created to correct student deficiencies in the subject area of algebra (Bader & Hardin, 2002). Tennessee high school students are required to take both Algebra I and Algebra II (Graduation requirements, n.d.).

Tennessee high school curriculum includes a course covering probability and statistics, but it is not required of all students to complete this course for high school graduation. MATH 1630, Finite Mathematics, is an algebra-based course. With all traditional and most nontraditional students having been exposed to algebra, an algebra-based learning support course is an appropriate subject pairing. However, the fact that the current corequisite course is not a viable support course for MATH 1530, Probability and Statistics, could stem from the absence of appropriate content in the subject area of statistics and basic probability in the corequisite learning support course. Evidence of success in prerequisite models may have been due to a strengthening of algebraic skills prior to students enrolling in MATH 1530, Probability and Statistics, leaving the student to focus on the subject at hand. Therefore, it is recommended that consideration be given to modeling a corequisite program modification after the Statway and Quantway pathways introduced by the Carnegie Foundation for the Advancement of Teaching during the 2009/2010 academic year (Merseeth, 2011). The reason these two pathways are being recommended as models is because of the successes of each model in providing students with the remediation and support needed to successfully complete college level mathematics courses. Mangan (2013b) stated that 51% of students who participated in Statway pilots at 21 colleges in 2012 earned college level math credit, compared to the 41.2% success rate of students taking MATH 1530, Probability and Statistics using Learning Support Model 3 in this study. Collins (2013) stated that the success rates of students at institutions where the Quantway program was 56%, which is slightly higher than the 47.6% success rate of students taking MATH 1630, Finite Mathematics, using Learning Support Model 3 in this study. Another reason for using the Statway and Quantway pathways is they are now endorsed by the Complete College America organization (Vandal, n.d.). Given the influence the organization has had on the corequisite

remediation movement and the fact that Tennessee is one of the 33 states that comprise CCA's Alliance of States (Complete College America, n.d.), the organization's endorsement of the Statway and Quantway pathways may provide the leverage needed to convince Tennessee Board of Regents leadership to allow the adoption of learning support models patterned after these pathways.

It is also recommended that serious consideration be given to creating an alternative pathway for nontraditional students and students who scored below 15 on the mathematics section of the ACT exam, or below the equivalent on the SAT and ACT Compass exams. Nontraditional age students who are years removed from their last mathematics course do not retain those skills as readily as in the reading and English subject areas (Boylan, 2011). Traditional age students who score below 15 on the mathematics section of the ACT exam have a serious deficiency in the skills required to successfully complete college level mathematics courses. According to ACT, the cumulative percentage of scores below 15 is 7% (ACT Profile Report-National, 2015). This population is a small in size, but the level of underpreparedness is large. Students who make less than 15 lack the ability to substitute whole numbers for unknown variables in algebraic expressions, they cannot effectively solve one-step equations, and lack the ability to combine like terms in preparation for balancing algebraic equations (ACT College and Career, n.d.). Students who fall into this population do not need a corequisite refresher. They are in dire need of an in-depth prerequisite course to advance their skills to a higher level before they are immersed into college level coursework.

While Florida's remedial education program that was designed to meet State Bill 1720 legislation, (Fain, 2013a) has received criticism, the program includes one positive component. Florida's remediation plan requires students needing remediation to be advised of their

developmental options. Students are then allowed to enroll in the option of their choice. While only 20% students who ignored the advice of counselors and opted out of remediation passed with a grade of C or better, students who heeded the advice of counselors experienced a 70.5% success rate (Smith, 2015c). By allowing students the option for a different form of remediation, many will choose an option similar to Learning Support Models 1 or 2 if they are informed of their chances of success based on their ACT scores, age, or enrollment status as evaluated in this study.

Based on the success of Florida's single semester prerequisite model, it is recommended that creating a pathway similar to Learning Support Model 2 be seriously considered. Following the Learning Support Model 2 model provides a pathway where students can complete a prerequisite course regimen in a single semester, thereby avoiding the pitfall of student discouragement due to the requirement of successive semesters of remedial coursework. It is also recommended that, along with the pathway creation, a procedure be established to properly advise students of the learning support options including the sharing of pertinent success data relative to ACT, Sat, and ACT Compass exam scores.

Recommendations for Future Research

As part of the literature review for this study a 2004 ACT Policy Report indicated that several nonacademic factors were more important in terms of student retention and completion at the college level than the often cited academic factors of high school GPA and ACT assessment scores (Lotkowski et al., 2004). In 2013 the Educational Testing Service (ETS) introduced an assessment called SuccessNavigator (Fain, 2015b), which is an instrument used by institutions to identify students with deficiencies in study skills, external support, and other nonacademic factors as highlighted in the 2004 ACT study. The need for remediation in the state of Tennessee

is based solely on ACT, SAT, or ACT Compass scores. However, Fain (2013b) indicates that such exam scores do not measure the drive, motivation, and commitment of each student, nor do these scores provide insight to other nonacademic factors that play a role in student success. This study was focused on the results of these assessments and took into consideration no factors of a non-academic nature.

As the data was processed during this study, an inconsistency in the results was noticed. One would expect students in learning support model LS3 who scored 17 and 18 on the mathematics section of the ACT exam (research questions 3 and 4) to have higher rates of success than those who scored 15 and 16 on the mathematics section of the ACT exam (research questions 5 and 6) because higher ACT scores are expected to reflect higher levels in algebraic skills (ACT College and Career, n.d.). Because the opposite in this case occurred, there must be factors influencing student success that could not be quantified using the archived data supplied for this study. Therefore, it is recommended that a qualitative study be undertaken, using the results published in the ACT Policy Report as a guideline to determine the influence of nonacademic factors on student success in mathematics, especially when remedial education is required. Nonacademic factors such as academic related skills (time management, note taking skills, study skills, etc.), academic self-confidence, academic goals and social support networks are difficult to quantify, making the use of a qualitative study ideal for evaluating such factors. While many institutions use the SuccessNavigator instrument to pinpoint potential issues related to nonacademic factors that affect student success, Walters State Community College uses the Survey of Entering Student Engagement, or SENSE assessment. This assessment could be administered to students entering developmental coursework at the beginning of the semester, used to predict student success, and later assess the ability of the assessment to predict student

success. The ability to enter into the study proactively also allows for the collection of interval data, providing the opportunity for a mixed method assessment model. Such information could yield a more viable method of determining student remediation needs, allowing for the design of a more robust remediation model to further increase student success.

Second, using archived data limited the study to the use of ordinal data. If interval data had been available in the form of final course averages, the statistical analyses may have yielded different results. For example, regression analyses can be performed with final grade averages instead of letter grades, which could yield predictable models that can enhance student advising based on ACT scores and student performance on additional diagnostic testing. Also, the study did not allow for the concurrent running of the various learning support models. This opened the study to influences related to other changes in academia that could have affected the outcome of the study. There are options for conducting follow-up studies where interval data can be collected and analyzed to determine the impact of various learning support models on student success in college level mathematics courses. One recommendation is to perform an experiment over the course of an academic year, comparing the student success in a college level mathematics course where the student participated in a single semester prerequisite remediation course versus the student success in the same college level course using a corequisite learning support course. The same data would be collected, replacing the letter grades with end of course grade averages. This would allow the use of analysis of variance to evaluate each research question. Using statistical analysis on interval data allows for a statistical procedure called the power determination to be performed. While the Holm's Sequential Bonferroni Method provided the means to reduce the potential of Type I error in determining statistical significance for those research questions where the null hypotheses were rejected, there were no provisions to address

the potential of Type II error. Type II error is defined as not rejecting the null hypothesis when, in actuality, a statistical difference exists (Gitlow & Levine, 2005). This situation normally occurs when sample sizes are not large enough to indicate significance. For example, there were only 13 students in the Learning Support Model 4 population in research question 16. Comparing this sample size to the populations of Learning Support Model 1 (264 students), Learning Support Model 2 (67 students), and Learning Support Model 3 (87 students), the risk of not identifying statistical significance due to the small sample size of what proved to be the most successful learning support model at 69.2% is possible. With interval data the power determination can be used to verify the sample size is sufficient in two way hypothesis testing so that Type II errors are avoided. While this follow-up study would yield useful information, it would only address the models currently in use, Learning Support Models 3 and 4.

To include the influences of prerequisite remediation models Learning Support Models 1 and 2, it is also recommended that a study be commissioned to simultaneously evaluate all four learning support models. While the study would be more difficult to execute, it would remove any external influences related to possible time-based influences, and will provide the opportunity to harvest interval data that can be evaluated using statistical tools intended for population mean and variance evaluations, which may yield more definitive results.

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