ALEKS

Information for Parents & Recent Publications

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Introduction

ALEKS was developed in the 1980's by researchers at the University of California and New York University with the support of a multi-million dollar National Science Foundation grant. Since then, its use has expanded steadily and its effectiveness has been borne out by many research studies. These three articles are just a small selection of the many scholarly and popular articles available on the subject of ALEKS. For more information, including more research studies, please go to www.aleks.com. Below you can see short summaries of the articles. The full text versions of these articles are attached.

SAT Prep Course Available – see attachment

Brief Summaries of Attached Articles

"**New Artificial Intelligence Systems for Improving Student Math Skills: Assessment and Learning in Knowledge Spaces (ALEKS)**,", 07/2009, Techrepublic.com

This research, funded by the National Science Foundation and published by the University of Alabama, demonstrated that a blended model -- utilizing both ALEKS and an instructor in a classroom -- is an effective tool for increasing facility in higher mathematics and decreasing the number of freshmen who leave math-intensive disciplines because they become discouraged by work they perceive as too difficult for them. This article emphasizes the importance of having a teacher monitor students and provide them with academic support as necessary, just as the Conserve School program does. It also notes that ALEKS provides students with a valuable opportunity to develop independence and self-discipline because it forces students to focus and engage actively with the material. ALEKS causes a transformation in the efficiency of student time and effort, the authors argue, because it replaces ineffective, passive "study sessions" with effective, active "learning sessions."

"**The Effects of a Computerized-Algebra Program on Mathematics Achievement of College and University Freshmen Enrolled in a Developmental Mathematics Course**," 12/2006, Texas A&M University dissertation. PDF available through Texas A&M University at http://repository.tamu.edu. (Only the abstract is attached because the complete dissertation is over 200 pages.)

In this study, ALEKS was found to be just as effective as traditional instruction. In addition, the researchers found that ALEKS was associated with a reduction in students' math anxiety and an overall improvement in students' attitudes toward math. Traditional instruction was not associated with improvement in anxiety or attitudes.

"**Smart ALEKS**," 4/2013, Edtechdigest.com

In this interview, excerpted in a web publication, the CEO of ALEKS explains that ALEKS provides more precise individualization of instruction for each student than competing programs because it uses a unique and sophisticated artificial intelligence application. Over a million students now use ALEKS in the U.S. each year. Research consistently demonstrates the effectiveness of ALEKS in comparison to traditional methods of math instruction.

Mastery of SAT Math *

MASTERY OF SAT MATH

Mastery of SAT Math is designed to help the student achieve mastery of the math topics on the SAT Reasoning Test.

We recommend the following use of this course by students preparing for the SAT:

- Master 100% of the material in this ALEKS course; and
- Take a number of SAT practice tests (widely available from other sources).

ALEKS individualized assessment and learning enables students to efficiently refresh and fill gaps in their knowledge of the mathematics tested on the SAT. The course works best when supplemented with SAT practice tests, so that students achieve fluency in the particular style and format of the SAT test questions.

This course covers the topics shown below.
Students navigate learning paths based on their level of readiness.
Institutional users may customize the scope and sequence to meet curricular needs.

Curriculum (396 topics + 99 additional topics) [open all | close all] PDF

- **Arithmetic Readiness** (28 topics)
- **Real Numbers** (28 topics)
- **Linear Equations and Inequalities** (45 topics)
- **Lines and Systems of Linear Equations** (34 topics)
- **Exponents, Polynomials, and Quadratics** (54 topics)
- **Functions and Sequences** (29 topics)
- **Rational and Radical Expressions** (54 topics)
- **Perimeter, Area, and Volume** (36 topics)
- **Lines, Angles, and Triangles** (35 topics)
- **Polygons, Circles, and Similarity** (27 topics)
- **Statistics and Probability** (26 topics)
- **Other Topics Available** (99 additional topics)

Other Topics Available
By default, these topics are NOT included in the course, but can be added using the content editor in the Teacher Module.

THE EFFECTS OF A COMPUTERIZED-ALGEBRA PROGRAM ON MATHEMATICS ACHIEVEMENT OF COLLEGE AND UNIVERSITY FRESHMEN ENROLLED IN A DEVELOPMENTAL MATHEMATICS COURSE

A Dissertation

by

JUDY M. TAYLOR

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2006

Major Subject: Curriculum and Instruction

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Approved by:

Chair of Committee,	Robert M. Capraro
Committee Members,	Mary Margaret Capraro
	Bruce Thompson
	Don Allen
Head of Department,	Dennie L. Smith

December 2006

Major Subject: Curriculum and Instruction

ABSTRACT

The Effects of a Computerized-Algebra Program on Mathematics Achievement
of College and University Freshmen Enrolled in a Developmental Mathematics
Course. (December 2006)

Judy M. Taylor, B.S., East Texas Baptist University;
M.Ed., Texas A&M Texarkana
Chair of Advisory Committee: Dr. Robert M. Capraro

We face a world in which a college degree increasingly dictates the likelihood of life success. At the same time, there has been an ever-increasing population of students who have not been prepared adequately through their high school education to meet the rigors of college/university-level content. This problem can be seen in the number of students needing Intermediate Algebra. Students who complete remedial courses with a grade of C or better are more likely to pass their first college-level mathematics course and continue their education until they have completed all coursework needed for a degree.

Students entering colleges and universities underprepared for collegiate mathematics, reading, and writing have reached epidemic proportions, with 30% of the students needing remediation in one of these areas. A portion of this problem has been identified as mathematics anxiety. Because students have habituated mathematics failure, they are aware of their deficiencies, but still desire a college education. They

bring with them years of negative emotions from repeated mathematics failures. These years of negative feelings about mathematics precipitated by repeated failures are often manifested as mathematics anxiety that must be addressed in order to improve students' content knowledge.

The purpose of this study is to investigate the effects of a web-based technology centric course, Assessment and Learning in Knowledge Spaces (ALEKS), on the remediation of college freshmen enrolled in an Intermediate Algebra class as compared to college freshmen enrolled in an Intermediate Algebra class taught using a traditional lecture method. Mathematics anxiety and attitude toward mathematics will also be investigated to determine if ALEKS can lower the anxiety associated with mathematics, as well as improve attitudes. An algebra test, mathematics anxiety rating scale, and mathematics attitude test was given to both groups of students at the beginning of the semester and at the end of the semester.

The overall findings of this research suggested that ALEKS Intermediate Algebra students performed as well as the Control group taking a class in Intermediate Algebra taught by lecture. The anxiety of the Experimental group decreased more than the Control group, and the Experimental group's attitude toward mathematics increased at a greater rate than did the Control group.

DEDICATION

Thank you to my husband, David, and my children, Alicia, Amber, and April, along with my parents, brother and sisters, and friends for their continued support and for all that they have taught me.

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Of course, none of my accomplishments would have been possible without the assistance and support of my family and friends. Thank you to my parents for raising me to believe I can accomplish whatever I set out to do. Thank you to my sisters, Sandra, Linda, Amy, Emily, and my brother, Haze. Thanks for the long talks on the phone while I was making that 5-hour drive to and from College Station. You kept me safe on many of those drives. I would like to thank you for your encouragement and allowing me to talk about what I was going through, even though you may not have understood.

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CHAPTER I

INTRODUCTION

With the proliferation of developmental students, colleges and universities must be certain effective teaching methods and programs are created so that underprepared students can gain the knowledge necessary to complete a rigorous post-secondary education. The present study was designed to explore the differences of underprepared college freshmen in an Intermediate Algebra course using different teaching approaches based on students' demographics, algebra test, mathematics anxiety, and mathematics attitude.

Research Questions

This study focused on the following research questions: (I) Does a mastery learning perspective of remediation, where students are expected to learn all the objectives in an Intermediate Algebra class, make a difference in mathematics achievement? (II) What differences exist between students using Assessment and Learning in Knowledge Spaces (ALEKS) compared to students who are taught Intermediate Algebra using a traditional lecture style? (III) Are there differential mathematics effects for either group based on demographic factors such as gender, age, ethnicity, number of mathematics courses taken in the past, and degree plans? (IV) Do differences emerge between the two groups of students in their perceived level of mathematics anxiety? (V) Is the student's attitude toward mathematics a factor in the student's inability to be successful in Intermediate Algebra? (VI) Is there differential

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This dissertation follows the style of *Educational and Psychological Measurement*.

performance between students who use ALEKS and Control group counterparts, and are there measurable differences one, two, and three years after completing the program?

Background

A major problem facing colleges and universities is a large percentage of students entering their freshman year ill prepared for mathematics undertakings. Sixty-seven percent of high school students earn a traditional diploma, while only 43% of those students graduate high school with college-entry skills (McDade, 2000). Seventy-six percent of the colleges and universities in the year 2000 that enrolled freshmen offered at least one remedial reading, writing, or mathematics course. Remedial classes are offered at 100% of community colleges, 80% of public four-year institutions, and 59% of private four-year institutions (National Center for Education Statistics (NCES), 2003a).

Nationally, one-third of incoming freshmen had to take at least one remedial class in reading, writing, or mathematics (National Commission on Excellence in Education (NCEE), 1998; NCES, 1996). Of the students taking remedial college-level mathematics classes, less than one in six students actually earn an academic associate’s or bachelor’s degree. More than one-third earns an occupational associate’s degree or certificate (Boylan & Saxon, 2004; Cross, 1971; Cross, 1976; Maxwell, 1979; McDade, 2000).

Underprepared students bring with them years of failure, especially in mathematics (Jones, Wilson, & Bhojwani, 1997; Paravate, Anjaneyulu, & Rajan, 1998; Strawser & Miller, 2001). The students are afraid of mathematics and are convinced that success in a mathematics class is unattainable because of past failures. Students believe that they are not capable of learning mathematics and they are destined for failure. They tend to give up quickly when confronted with difficult mathematics tasks (Jones et al., 1997; Paravate et al., 1998; Strawser & Miller, 2001). Underprepared students will enter college knowing their deficiencies but with a desire to work toward and achieve a college education (Jones et al., 1997).

Rationale

Remediation of college freshmen is a topic that has been discussed for decades, but for most of the century remedial courses has not been the subject of serious research. Because remedial education is viewed as a solution to a problem, no one views it as a valuable undertaking (Boylan, 1995; Boylan & Saxon, 1999; Casazza, 1999; Roueche, 1968; Roueche, 1973; Roueche & Baker, 1983; Roueche & Kirk, 1974; Roueche & Snow, 1977; Roueche & Roueche, 1993; Roueche & Roueche, 1999).

Thirty percent is the national average for the students entering college not ready to enroll in a college-level mathematics course who will need to take a developmental mathematics course (NCEE, 1998). A review of individual Texas universities shows that some of those percentages are as high as 80% with an average of 28%, and some Texas community colleges are as high as 80.6% with an average of 50.6%. This is slightly higher than the national average of 42% for community colleges (Texas Higher Education Coordinating Board, 1999; National Center for Educational Statistics, 2000). Although these students have been in school for thirteen years and have attended classes in mathematics, they will not have the skills needed to be successful in a college-level mathematics class.

A review of the literature in developmental education has been done to identify information on remedial instruction and related topics (Boylan & Saxon, 1999; Boylan & Saxon, 2004). “Among the variables over which developmental educators have control, the quality of classroom instruction is the single most important contributor to the success of developmental students” (Boylan, 2002, p. 2). Best practices for developmental students are instructional learning communities, varied teaching methods, supplemental instruction, frequent testing opportunities, use of technology, frequent feedback, mastery learning, critical thinking, and learning strategies (Boylan, 2002; Cross, 1976).

Thirty percent of students enrolling in colleges and universities will need remediation. The question is “What is the best way to remediate these students?” The fact that most of these students have been taught by lecture method and still need remediation argues strongly that lectures have not worked for these students. Teachers at the university level must find teaching methods that will interrupt students’ cycle of poor mathematics performance.

Effective Instructional Strategies

The need for effective instructional strategies to educate the large number of students who need remediation when they enroll in colleges and universities must be addressed. Some issues include the following:

1. Ineffective remedial programs that require too much time to effect progress toward regular college courses.

2. Mathematics anxiety is directly related to unsuccessful attempts at mathematics mastery.

3. Negative mathematics attitudes mediate mathematics performance.

Keup (1998) suggests that a strategic plan must be devised to interrupt the students' cycle of poor mathematics performance. That plan must implement effective remedial programs that prepare students for rigorous college courses in an appropriate amount of time. Part of the problem is anxiety is presumed to be a factor in students' inability to learn mathematics or their inability to pass mathematics tests and their perception of mathematical inadequacies (Jones et al., 1997; Robert, 2002; Scott, 2001; Steele & Arth, 1998). Findings by Goolsby, Dwinell, Higbee, and Bretscher (1988) indicate that a student's confidence in their ability to learn mathematics was the only variable included, which contributed to prediction of performance in a developmental mathematics course (Goolsby et al., 1988). Students in developmental classes would benefit from a plan to increase confidence and lower the level of anxiety associated with mathematics.

Research has shown that underprepared students need a variety of teaching methods (Boylan & Saxon, 1999; Strawser & Miller, 2001). Some of the innovative approaches are freshman seminar/orientation courses, Supplemental Instruction, paired or adjunct courses, collaborative learning communities, and critical thinking courses and programs (Benander, Cavanaugh, & Rubenzahl, 1990; Boylan, 1999b). The freshman seminar is a course that lasts all semester long instead of a day or two at the beginning of the semester and deals with issues such as college life, purpose of higher education, and study skills (Boylan, 1999b; Moreno, 1997; Rhodes & Carifio, 1999). In Supplemental Instruction, courses that students traditionally have difficulty with are labeled “high risk” courses and are usually courses where 30% of the students receive a D or F. The courses that are high-risk courses are assigned a student that has already taken the class and passed it; they attend the class and serve as a group leader for any student needing help (Boylan, 1999b; Henson & Shelley, 2003; Maxwell, 1998; Ramirez, 1997; Stansbury, 2001). Small groups of students form learning communities to help developmental students be successful. These learning communities meet regularly outside of class to support each other (Boylan, 1999b; Davies, Ramsay, Lindfield, & Couperthwaite, 2005). Paired courses are to some degree like the learning communities with the addition of taking two courses, one that supplements the other (Boylan, 1999b; Sills, 1991). Critical thinking instruction is just classes that help students learn to think critically. Strategic learning helps students understand how to transfer knowledge to other courses (Boylan, 1999b; Brookfield, 2005). Underprepared students are diverse groups needing innovative teaching methods (Saxon & Boylan, 1999).

The instructional needs of college freshmen that need remediation must be addressed. Research has shown the number one factor that affects student achievement is the teacher (Roueche & Roueche, 1993). Teachers must know their students’ needs and their difficulties with mathematics so the teacher can change teaching strategies to meet the students’ needs. To combat the anxiety associated with the learning of mathematics, teachers must work on their own attitudes as well as the attitudes of their students (Adeeb et al., 1998; Black, 1998; Donlevy & Donlevy, 1997; Schwartz, 2000). If a student does not understand the concepts being taught, then the teacher must find a way to communicate those concepts through non-traditional strategies (Adeeb et al., 1998; Black, 1998; Donlevy & Donlevy, 1997; Schwartz, 2000). Students need to know that the teacher believes in them and that they can be successful as long as they do not give up (Adeeb et al., 1998; Black, 1998; Donlevy & Donlevy, 1997; Schwartz, 2000).

Research has shown that students' achievement can be directly correlated to teachers' beliefs (Roueche & Roueche, 1993). Teachers must change their beliefs about which students in their classroom have the ability to learn mathematics. Some teachers do believe that teachers and schools are the keys for student learning, while others believe that student learning is attributed to the students' own abilities and background experiences (Allexsaht-Snider & Hart, 2001).

Underprepared students can achieve success in their post-secondary education provided educators follow the guidance of the teaching strategies used in effective schools. Effective schools research has shown that underprepared students need to see clear precise examples that have meaning (Boylan & Saxon, 1999; Cornell, 1999; Schwartz, 2000; Strawser & Miller, 2001), that immediate feedback is essential for student success (Jones et al., 1997), and students gain confidence from having completed a problem correctly (Black, 1998; Stipek, Givvin, Salmon, & Macgyvers, 1998). Effective schools research also suggests that revisiting previous concepts with your students will allow them to see that mathematics builds on previously learned concepts. Using these approaches can help students build a more positive attitude about learning mathematics and reduce anxiety associated with mathematics classes (Schwartz, 2000;

Steele & Arth, 1998).

The use of mastery learning can be a significant factor for college and university developmental students who struggle with mathematics (Boylan & Saxon, 1999; Juhler, Rech, From, & Brogan, 1998; Strawser & Miller, 2001). Computer-based mastery learning has been researched for the past decade and findings indicate positive effects. The positive effects of computer-based mastery learning included more students learning in less time, slightly higher grades on posttests, and improved student attitudes toward learning (Kulik & Kulik, 1986). Roeuche and Roueche (1999) found that students who used computers for writing assignments and as a tutor for mathematics contributed to their success in remedial courses.

The focus of this study is the effect of a web-based, computer-assisted curriculum based on mastery learning of intermediate algebra in remedial mathematics compared with students in a lecture class. This study will look at differences in student achievement in a web-based, computer-assisted curriculum in remedial mathematics classes as compared to classes that use a traditional lecture method of instruction. The study will also examine the effects each treatment has on mathematics anxiety and mathematics attitude.

Variables

The independent variables in this study are gender, age, ethnicity, and mathematics courses taken in the past. The dependent variables are National Achievement Test, First Year Algebra Test (NATFYAT) (Webb & Hlavaty, 1962), mathematics anxiety rating scale (MARS), and mathematics attitude scale (MA). The

NATFYAT is a 48-question algebra test written by Webb and Hlavaty in 1962. The MARS is an instrument to measure the level of mathematics anxiety that students have. It has 30 questions written by Suinn (1972). The MA is a 47-question survey that measures the attitude of students on students' confidence in mathematics, teacher effect, usefulness of mathematics, and male dominance in mathematics written by Fennema and Sherman (1976).

Study Considerations

One possible limitation to the present study encompasses the characteristics (i.e., underprepared, anxiety, and fear of failure) of the developmental students who are being studied. These students do have anxiety associated with the learning of mathematics, have been failures in mathematics their entire school experience, and they have tendencies to give up when difficult problems have been presented, it is expected that a low response rate is a warranted concern, meaning the final participants may not actually represent the population to which inference is desirable, thus the limitation (Jones et al., 1997; Robert, 2002; Scott, 2001; Steele & Arth, 1998). Students may not have taken the time to work the mathematics problems simply because they found them difficult and felt that they could not successfully complete the problems accurately and simply guessed. This would be true of the pretest as well as the posttest for all students in the study.

Definitions

The terms and definitions used in this study are listed below:

<u>ALEKS</u> - Assessment and Learning in Knowledge Spaces is an Web-based

curriculum designed for the remediation of mathematics concepts (ALEKS, 2001).

Computer-based Instruction - This type of instruction is completely administered by an Web-based system with the instructor acting as a facilitator (ALEKS, 2001).

Lecture Method - An approach to teaching where the teacher stands in front of a group of students and talks about some subject to impart knowledge.

Mathematics Anxiety - Fear of failure associated with unsuccessful attempts at working mathematics problems (Schwartz, 2000).

Mastery Learning - A methodology of utilizing small units of instruction and frequent testing and requiring students to be able to master one unit before progressing to the next unit (Boylan & Saxon, 1999).

Remediation - Coursework offered at a postsecondary institution (either community college or four-year) that is below the level of college credit work. It is also known as “developmental education,” “basic skills training,” or “nontraditional coursework.” This coursework is intended to correct deficiencies or improve skills in certain areas of learning.

CHAPTER II

REVIEW OF THE LITERATURE

Introduction

Students entering college underprepared bring with them attitudes that create issues of mathematics anxiety, and years of failure in the acquisition of mathematics knowledge. The students' anxiety and attitudes must be considered in addition to the curriculum and best practices in the development of these students.

Access to Higher Education

Cross (1971) describes three periods of the higher education movement: aristocratic, meritocratic, and democratic. The focused topic for each period was access: who should go to college, and more recently, which college should students attend (Roueche & Roueche, 1993).

In the 19th century, higher education was reserved for the privileged few. Most students were the children of aristocrats and would eventually inherit their parents' wealth and social status. Attending college would assure the students' status in life. Only men attended these colleges and society dictated that the poor, the ethnic minorities, and women would not need a college education (Brubacher & Rudy, 1997; Roueche & Roueche, 1993).

College educators fought against the philosophy that attendance in college was a birthright. These educators felt that college education was an earned right. The Morrill Land Grant Acts in 1862 and 1890 opened the doors of education to a more diverse population but still did not admit minorities (Land-Grant History and Institutions, n.d.).

Land-grant colleges took up some of the same notions as the elitist colleges in that students were admitted as long as students had academic merit--those students who showed the most promise to be successful in higher education, thus--meritocracy (Brubacher & Rudy, 1997; Cross, 1971). Meritocracy reached its peak during the 1950s. Colleges and universities looked for the talented students based on students' merit (Cross, 1971). Scores made by the students on the ACT and the SAT achievement tests (Boylan, 1999a; Popham, 2006) have measured merit.

The belief that only the most promising should be allowed a college education led to a more democratic view of higher education called "the open door policy." The open door policy simply means all students are welcome to enroll and attend these colleges. To address the open door policy, junior colleges became an enormous part of higher education, although some universities and private colleges also have open door policies (Brubacher & Rudy, 1997; Cross, 1971; Roueche & Roueche, 1973; Roueche & Roueche, 1993).

The Need for Remedial Mathematics Education at the College Level

The open door policy has encouraged many more students to pursue a college education, even though the student may not be academically prepared. In fact, students entering their freshman year underprepared for mathematics, reading, and writing have reached epidemic proportions with 30% needing remediation in these areas of study as reported in "A Nation Still at Risk" (National Commission on Excellence in Education (NCEE), 1998; National Council of Education Statistics (NCES), 1996; Texas Higher Education Coordinating Board, 2002). Some of the percentages in Texas universities are as high as 80%. The percentages for community colleges in Texas are as high as well (Texas Higher Education Coordinating Board, 1999; National Center for Educational Statistics, 2000).

The 1995 survey shows that 78% of higher education institutions and 100% of public two-year institutions that enroll freshmen offered remedial courses. The Maryland Higher Education Commission reported that 40% of students who completed college-preparatory courses in high school and immediately attended a community college needed mathematics remediation. The institute's goals are improving the effectiveness of remedial education in higher education and reducing its need in higher education (Waycaster, 2001).

Issues and Their Relationship to Developmental Education

The problem of remediation is not a new phenomenon. The subject of remediation has been debated for 175 years. Brubacher and Rudy (1997) report that during colonial times, students were required to know only Greek and Latin. There was no formal secondary education; students would have a personal tutor or a local minister would give instruction. Harvard requirements were to pass an oral, exam as well as a written exam, in Latin. Yale, William and Mary, New Jersey, and King's College followed exactly the same original requirements as Harvard. It was not until 1745 that a new subject, arithmetic, was formally added to the entrance exam (Brubaher & Rudy, 1997). Europe viewed American institutions (i.e., Yale and Harvard) of higher education as only a college, a preparatory school, not a true university (Brubacher & Rudy, 1997).

To illustrate the misunderstanding and anxiety of earlier times of underprepared students, a story comes from Cornell University during the 1800s. The founder, Ezra Cornell, asked the professor responsible for admission decisions why so many applicants were not passing the entrance exam. The admissions professor replied that the students did not know enough. Cornell then asked why the university could not teach the students what they needed to know. The admissions professor then replied that the teachers were not prepared to teach the alphabet. “Can they read?” asked Cornell. The admissions professor’s response was that if Cornell wanted the faculty to teach spelling, he should have founded a primary school (Brier, 1984; Casazza, 1999). Although this story does not address mathematics deficiencies in college students, it does document a period in history concerning underprepared students entering college.

In his 1852 inaugural address as President of the University of Michigan, Henry P. Tappan stated that American colleges were too much involved in teaching rudimentary courses that belonged in intermediate or even primary schools, and that the universities were lowering their standards by admitting poorly prepared students. He asked, “Of what avail could the learned professors and preparations of a University be to juvenile students? To turn raw, undisciplined youth into the University to study the Professions, to study the Learned Languages and the Higher Sciences is a palpable absurdity” (Maxwell, 1979, p. 7).

The dialogue concerning underprepared college students continued with Charles Eliot, Harvard University’s President in 1871. Eliot was concerned that the freshmen entering Harvard could not spell correctly, could not express thoughts efficiently, and were unable to use rules of punctuation. Because students were unable to spell and write complete thoughts correctly, an exam was developed to include written composition. Just eight years later, in 1879, 50% of the applicants were admitted “on condition” because they were failing the exam (Casazza, 1999). Harvard first offered freshman English in 1874 at the request of faculty members who were dissatisfied with students’ preparation in formal writing (Maxwell, 1979). Like Cornell, this story does not address mathematics difficulties, but continues the discussion of the large number of students entering college underprepared for college work at prestigious private universities.

In the mid nineteenth century, there was discontent with the traditional liberal-arts college of America. In 1850, the United States had 120 colleges, 47 law schools, 42 theological seminaries, and not a single school of higher education designed for the agriculturalist, the manufacturer, the mechanic, or the merchant. These students desired to prepare themselves for their life’s work at an institution of higher education. The individual states did not have sufficient resources to develop this educational plan. Therefore, supporters of this movement sought federal support. The passing of the Morrill Acts in 1862 and 1890 directly addressed this discontent and opened the door for a more diverse population than ever before (Brubacher & Rudy, 1997; Land-Grant History and Institutions, n.d.). These Acts introduced a new partnership in higher education: the federal government with colleges and universities (Brubacher & Rudy, 1997: Casazza, 1999; Dotzler, 2003).

Not only did government get involved, but business leaders also began seeking to influence curriculum development that would prepare students for specific professions (Brubacher & Rudy, 1997; Casazza, 1999). Executives felt that a college education was not a beneficial goal because a college education dealt too much on literary and classical studies. Colleges needed to be established to address the needs of the agriculturalist, the manufacturer, the mechanic, and the merchant, and to provide the students the education needed to prepare them for the profession that the student desired to devote their lives (Brubacher & Rudy, 1997; Casazza 1999).

Charles Eliot wanted to help solve the problem of underprepared college students. Because of Eliot's concerns in 1892, the National Education Association created the Committee of Ten to examine the curriculum of high schools and the requirements for admission to college (Casazza, 1999). Eliot and the Committee of Ten laid out the courses that every properly educated student should take, including mathematics and science. The Committee of Ten recommended that all courses be taught to all students as if they were college bound and to make all of these courses of equal rank for the purpose of college entrance. These recommendations seemed to take care of the dual role of secondary school (i.e., educating students who were and were not college bound) (Brubacher & Rudy, 1997). Charles Eliot's work with the Committee of Ten influenced the methods used in teaching school subjects for the next century (Hennessy, 2002). Eliot's view of the solution to the problem lay in the organization and curricula of elementary and secondary education (Tanner & Tanner, 1995).

The problems in elementary and secondary education were not solved, and soon after the turn of the century colleges and universities at all levels were offering developmental courses. "Remedial reading" and "study skills" were the most common terms used to indicate developmental courses. Soon preparatory departments were being created to meet the needs of underprepared students entering college. In fact, many of these departments were growing at such a rate that the number of students in the preparatory department exceeded the regular college enrollment (Brubacher & Rudy, 1997; Casazza, 1999; Dotzler, 2003). The decade 1850 to 1860 at the University of Wisconsin reached an enrollment of 300 only twice, and only 41 out of 331 were registered in regular college classes. The rest of the students were in the preparatory department, normal department, or were classified as specials (Brubacher & Rudy, 1997). By 1909, 350 colleges were offering "how to study" courses for underprepared students. Only eleven short years later, 100 study books had been published to address the issue of underprepared students entering college (Brubacher & Rudy, 1997; Casazza, 1999; Maxwell, 1979). In a survey sent to all state colleges in 1929, 25% of the respondents indicated that they tried to identify poor readers on admissions and only nine schools reported that they provided some type of remediation (Parr, 1930). One dean said, "I am sorry that we have nothing to report as done, but I am heartily delighted that you are beginning work along this line. I don't know anything more timely" (Parr, 1930, p. 548). For almost 150 years, educators have been attempting to address the problem of underprepared students; focusing first on reading and study skills, educators soon turned their focus to the lack of mathematical skills.

One of the most significant events happened after World War II with the offering of the GI Bill. The GI Bill was written with the assumption that very few would take advantage of it, but the bill actually inspired one million veterans to enroll in college by the fall of 1946 (Brubacher & Rudy, 1997; Casazza, 1999; Dotzler, 2003). Although many of these returning service members were originally considered underprepared, they "systematically outperformed their younger, selectively admitted classmates, and demonstrated a model of educational success that could come with greater maturity and a second chance" (McCabe & Day, 1998, p. 3). The success of the veterans created a great deal of optimism, which resulted in more Americans being granted access to higher education and the ever-increasing need of developmental classes (McCabe & Day, 1998). The GI Bill also contributed to the huge number of community colleges established during this time (Brubacher & Rudy, 1997; Maxwell, 1979).

College enrollment continued to increase over the years. A large increase in America's access to higher education came in the 1950s and 1960s with the advent of the Civil Rights Movement. Brown v. Board of Education and other court decisions struck down "separate but equal" facilities and segregation in schools at all levels (Brown v. Board of Education, 1954).

The 1957 launch of Sputnik created a sense of loss in that America could no longer boast of being the world's leader in technology. A national debate began over the need for reform in mathematics and science curricula. Young people of the United States were not learning enough mathematics (Hennessy, 2002).

Many colleges from 1963 to 1973 were able to be more selective in their admissions policies as the first students of the Baby Boom reached college age, so proportionately fewer underprepared students were admitted to four-year colleges (Boylan, 1995). Because colleges and universities could be selective about the students allowed to enter higher education, junior and community colleges grew rapidly throughout the country, providing access (often open admissions) to Americans who wanted to go to college. The number of underprepared students enrolling in junior and community college and universities would increase because of the open door policy (Boylan, 1995).

The first junior college began in 1901 as an experiment from Joliet Township High School in Illinois and later become Joliet Junior College. This happened because of the high school offering postgraduate courses to six high school students. Soon Joliet was asking and receiving advanced standing from graduate schools from Michigan and Illinois. Joliet Junior College did not become an official college until after World War II (Brubacher & Rudy, 1997). The growth of the community college has been phenomenal. In 1950-51 there were only 217,500 students attending community colleges. By 1960, the enrollment had increased to 453,600; in 1970-71, the enrollment was 2,227,200. In 1986-87, the number of students attending the 1,368 community colleges was 4,776,000. In the mid 1990s, there were about 1,500 community colleges with ten million students attending (Brubacher & Rudy, 1997).

By the 1970s, students entering college would no longer be described as the upper elite aristocratic part of society, nor would they be described as students with academic merit. Instead, students enrolling in colleges and universities were described as the first generation in their families to pursue education after high school, had scored in the lower third on traditional tests of academic ability, but saw education as the way to the American dream (Brubacher & Rudy, 1997; Casazza, 1999; Saxon & Boylan, 1999). This trend of underprepared students has continued to the present with colleges and universities accepting the fact that each year students will enroll underprepared, and the students' deficiencies will need to be addressed (Casazza, 1999).

Underprepared students will enroll in colleges and universities, and these students will need assistance. That need has created tension in that some colleges and universities would provide access to all students, while others fear open access will lower standards. There will always be students who are capable of succeeding, but are in need of help (Casazza, 1999).

Profile of the Developmental Students

Developmental students are described as follows: (a) graduated from high school with a low C average or below, (b) scored in the bottom third of their class on standardized tests, (c) are deficient in basic skills, (d) have poor study habits, (e) are not highly motivated, (f) have no encouragement from home, (g) have unrealistic and ill-defined goals, (h) come from homes with minimal cultural advantages and minimum standards of living, and (i) are the first in their family to attend college. The fact that these students are the first in their family to attend college means the student has a minimum understanding of what college requires or what opportunities it offers (Roueche, 1968; Roueche & Roueche, 1993).

Well into the 1970s, the profile of the developmental student had not changed much for more than 45 years. Most were Caucasians from blue-collar families (Cross, 1971; Roueche & Roueche, 1993; Saxon & Boylan, 1999). Nationally, 67% of developmental students are Caucasians (Saxon & Boylan, 1999). A large number of the rest were members of ethnic minority groups (i.e., African American 23%, Hispanic 6%, Asian 3%, and American Indian 1%) (Boylan, Bonham, & Bliss, 1994; Saxon & Boylan, 1999). The average age of community college developmental students were 23 with 59% under the age of 24, 24% were between the ages of 25 and 34, and 17% were over the age of 35 (Boylan et al., 1994; Saxon & Boylan, 1999). Fifty-five percent of female students were developmental students compared to 45% of male students. Married students account for 22% to 28% of the population (Boylan et al., 1994; Saxon & Boylan, 1999). Most had parents that had never attended college; the students had not been very successful in high school, but viewed college as a way to a higher paying job and a better way of life (Cross, 1971; Roueche & Roueche, 1993).

Today's developmental student can be described with some of the same phrases. Generally, the students have little or no support from home, are first-generation college students, have been described as failure expectations, have little academic success as they begin their college pursuits, have weak self-concepts, and have to work 30 hours each week to support themselves (Roueche & Roueche, 1993). Fifty percent of developmental students report that they are financially independent. Fifty-four percent of those financially independent students report having an annual income of $20,000 (Boylan et al., 1994; Saxon & Boylan, 1999).

Developmental versus Remedial

While the condition is well understood and clearly articulated, the terminology has been a source of controversy among stakeholders. Some educators say the word remedial implies brokenness and suggests that something, or someone in this case, is in need of repair. Cross (1976) distinguishes between the word "remediation" and developmental by stating:

Developmental is frequently used as a euphemism for remedial in a dim awareness that developmental education is the more enlightened term to use. The distinction between remedial and developmental education lies in the pedagogical sophistication of the approach. In my view, a more useful distinction is found in the purpose or goal of the program. If the purpose of the program were to overcome academic deficiencies, I would term the program remedial. If, however, the purpose of the program is to develop the diverse talents of students, whether academic or not, I would term the program developmental (p. 31).

Other educators prefer the word developmental to describe students who have entered colleges underprepared; developmental has a more positive meaning, which focuses on change and growth and does not focus on the deficiencies of students (Boylan, 2002).

Competing Views

As previously stated, there are two theoretical frameworks. One framework views underprepared students as a whole person that needs emotional and social, as well as academic support, and the other framework views these students as broken and in need of fixing (Boylan, 1995; Casazza, 1999; Cross, 1976).

The groups of people who view underprepared students as a whole person prefer to refer to these students as developmental and to refer to the courses these students take as developmental courses. Developmental education also addresses the idea of developmental mathematics, in that the percentage of students needing remediation in mathematics is greater than students needing remediation in reading or writing, as defined by the National Association for Developmental Education as:

> … a comprehensive process, which focuses on the intellectual, social and emotional growth and development of all learners. Developmental mathematics education includes, but is not limited to, tutoring, personal, and career counseling, academic advisement, and coursework. Developmental mathematics education is a field of practice and research with a theoretical foundation in developmental psychology and learning theory. It promotes the cognitive and affective growth of all learners, at all levels of the learning continuum. It is sensitive and responsive to the individual differences and special needs among learners (Casazza, 1999; National Association for Developmental Education (NADE) Executive Board Meeting, 1998).

Some of the assumptions about developmental education in this definition are: (a) it is a comprehensive process that looks at the student holistically, (b) it assumes that development is a process and looks at more than an increased score on a test as a measure of success, (c) it focuses not only on the intellectual growth of a student, but also on the student’s social and emotional development, (d) it has a very distinct feature in the assumption that all students have talents, and (e) it is not limited to learners at any particular level; even graduate students could be classified as developmental students needing the support of peers and instructors (Casazza, 1999). Developmental students are students who desire admission into colleges and universities, but are underprepared for college curriculum (Saxon & Boylan, 1999).

The term remedial is often used to describe students who are underprepared for college curriculum. This second view is that there is something wrong with the students and the students need to be diagnosed and fixed. The courses that these students must take are referred to as remedial courses. Even though the word “remedial” carries some negative connotation, the word continues to be used when referring to students who are underprepared. Remediation “is the most common term across educational levels to describe student weaknesses or deficiencies. It implies “fixing” or “correction” of a deficit” (Casazza, 1999, p. 4). Remediation is defined as coursework offered at a postsecondary institution (either community college or four-year college or university) that is below college-level work. It is also known as “developmental education,” “basic skills training,” or “nontraditional coursework” (Casazza, 1999). Often the idea that something is wrong is associated with the medical model where a diagnosis is made, a prescription is given, and there are follow up visits to see if the patient is healthy. With this view, students are referred to as remedial students and who take remedial courses. Examining the meaning of the word remedial reveals it is frequently used to describe student weaknesses and deficiencies. It implies that if the first course did not work, then maybe another course will be able to bring the student up to speed or maybe the student is asked to refill the prescription (enrolling in the same course for a second time) (Boylan, 1999; Casazza, 1999). “Colleges and universities do have a history of providing academic support to students who need assistance to perform well in a challenging academic environment” (Office of Higher Education, 1999).

Theoretical Framework

Developmental courses, especially mathematics courses, have grown rapidly in the community college in recent decades. According to a National Center for Educational Statistics (NCES, 1996) study, 99% of the nation's public community colleges currently offer remedial courses in one or more subject areas. Developmental mathematics courses are offered not only at community colleges but also at four-year colleges and universities. In fact, 81% of all four-year institutions offer some form of developmental education. According to the NCES study, 30% of all freshmen require developmental education (NCES, 1996).

Successful developmental programs are part of a centralized program. A centralized program is a department in itself and all courses come under the heading of developmental education, as opposed to the courses taught by the mathematics department (Boylan, Bliss, & Bonham, 1997; Stephens, 2001). The successful programs included regular program evaluation, student counseling and advising, and tutoring (Boylan et al., 1997; Boylan & Saxon, 1999).

Recent research has identified several other factors that contribute to successful developmental courses and programs. For instance, when classroom and laboratories were integrated, instructors and laboratory personnel worked together so that course objectives were supported directly by the laboratory activities (Boylan et al., 1997). Another factor has to do with institution-wide commitment to developmental programs and students by providing resources, public administrative support, and institutional acceptance of developmental programs and students as a mainstream activity for the college (Boylan & Saxon, 1999).

The use of learning communities was also found to improve the performance of students enrolled in developmental courses. Learning communities are groups or cohorts of students who take the same courses and their instructors function as a team to ensure that all students received the support and help needed to be successful (Boylan & Saxon, 1999; Humphrey, 2004; Watson, 2005). Tinto (1997) found that underprepared students who participated in a learning community had better attitudes toward learning and had higher completion rates than those in traditional developmental courses. University of California, Berkeley was the site of a study conducted in 1975-76 by Uri Treisman. He studied a group of 20 American students and 20 Chinese American students (Duncan & Thomas, 2000). The two groups had sharply contrasting success in calculus. The Chinese American students excelled, and the African American students failed. Treisman showed that the differences were not due to differences in motivation, inadequate academic preparation, lack of family support for higher education, or differences in socioeconomic status. The difference came in the two words “studying mathematics.” The African American students worked alone, rarely seeking help from other students or teaching assistants. The students had compartmentalized their life into academic and social. On the other hand, the Chinese students often met with other students to study, an activity that was part of their social lives. From the findings of his study, Treisman developed the Mathematics Workshop Program, intended to provide a group type setting for problem solving for students enrolled in introductory calculus (Duncan & Thomas, 2000). Even though this study does not address developmental students, it does address the importance of students studying together.

Another effective technique is called supplemental instruction, which simply is a small group of students from the course meeting with a student leader. The student leader is not enrolled in the class, but attends the class, takes notes, and then meets with the students to assist the students in the process of learning the material (Boylan & Saxton, 1999).

Several other techniques that have been successful include: (a) strategic learning; students had to recognize when they were not understanding a concept and then try another strategy for understanding, (b) professional training; teachers who work with underprepared students must be trained (Casazza, 1999; Damashek, 1999; Roueche, 1973), (c) student orientation, and (d) critical thinking. The emphasis of critical thinking has proven to be successful in improving the performance of developmental students (Boylan & Saxon, 1999).

Developmental courses and programs will be more effective when colleges and universities make a decision on how the institution will view the underprepared students – developmental or remedial. When students do not enter college prepared for the rigors of postsecondary mathematics pursuits, an intervention that interrupts their cycle of poor mathematics performance must be devised (Strawser & Miller, 2001).

Research to Support Developmental Efforts

John Roueche and his colleagues at the University of Texas, Austin developed effective techniques for providing remediation. The review of the literature indicates that between 1968 and 1978, Roueche and his colleagues published more books and articles on remedial education than did all other authors in the field combined. Therefore, any discussion of effective techniques, models, and methods for remediation must rely on the early work of Roueche and his colleagues (Boylan & Saxon, 1999).

Roueche and his colleagues identified aspects of learning theory that fit best with teaching developmental courses. Roueche (1973) argued that developmental instruction should be systematic and clearly based on what is known about how people learn. The learning theory of the time was behaviorism; therefore, behaviorist thinking influenced Roueche’s findings. Behaviorist techniques seemed to be successful with developmental students and that finding has been validated by further research (Boylan & Saxon, 1999; Maxwell, 1998; Roueche, 1968).

Another learning theory that is important for underprepared students is Vygotsky’s zone of proximal development. Vygotsky’s zone of proximal development says that what a student can do today with assistance, the student will be able to accomplish by himself tomorrow (Casazza, 1998; Cole, John-Steiner, Scribner, & Souberman, 1978). Vygotsky’s zone of proximal development “is the distance between the actual developmental level as determined by independent problem solving and the level of potential development as determined through problem solving under adult guidance or in collaboration with more capable peers” (Cole et al., 1978, p. 86). Intelligence is really related to performance following the mediation of guided instruction (Casazza, 1998). “Vygotsky’s framework outlining the effectiveness of an external mediator who gradually releases the responsibility of learning to the learner relates to the concepts of collaboration and constructivism” (Casazza, 1998, p. 19).

Constructivism has to do with how the learner understands what knowledge is (Casazza, 1998). Roueche found that successful developmental courses in mathematics used mastery learning, were highly structured, used a variety of teaching methods to accommodate varied learning preferences, and were based on cognitive theory (Stephens, 2001).

Alfred North Whitehead (1929) in his “Aims of Education” stated, “From the very beginning of his education, the child should experience the joy of discovery. The discovery which he has to make is that general ideas give an understanding of that stream of events which pours through his life, which is his life.” He went on to say the only reason to study the past is to equip us for the present.

Piaget’s theory is that the learner constructs understanding, and learns by doing. The world is interpreted, not just observed and imitated. A student will learn in his own time (Singer & Revenson, 1996). This theory, constructivism, allows students to construct learning of concepts by being directly involved with the process of understanding by using an application or modeling approach (Casazza, 1998). Many students who seek admission in college are still in need of assistance. The students’ background may explain this need for assistance.

Background of Developmental Students

The United States as a whole does fairly well in the elementary grades but somewhere between middle and secondary school, students do not learn the mathematics needed for success in iteratively more rigorous mathematics courses (National Commission on Excellence in Education (NCEE), 1998). Students’ failure to learn the mathematics needed for success is true of our advanced students as well as students in schools that are identified as ‘good’ schools (NCEE, 1998; Thomas B. Fordham Foundation, 1999). Trends in International Mathematics and Science Study (TIMSS) compared the mathematics and science achievement of half a million students in 41 countries in 1995. The results from the TIMSS show that United States fourth graders do fairly well compared to students in other countries, eighth graders are average to poor, and twelfth graders came in 19th out of 21 countries (Finn, 1998b), and the results for 2003 were very comparable (Ferrini-Mundy & Schmidt, 2005). We face the ever-widening gap between schools that produce students academically adept and schools that produce students who cannot read or write at the appropriate grade level. Therefore, some students meet curriculum expectations while many others graduate, barely able to read and write at the twelfth grade level (Allexsaht-Snider & Hart, 2001; NCEE, 1998; Thomas B. Fordham Foundation, 1999). As reported by the NCEE (1998), “poor and minority children, by and large, go to worse schools, have less expected of them, are taught by less knowledgeable teachers, and have the least power to alter bad situations. Yet it’s poor children who most need great schools” (p. 2).

Unfortunately, some educators and commentators do not believe the studies that show the mediocre performance of our teachers and students; they seem to be in denial. Instead of admitting that there are serious problems that need to be addressed, educators and commentators deny that there are any problems at all. Many educators seem to think some students, especially those born to socioeconomically challenged homes, just cannot be expected to learn much. James Coleman, under the Johnson Administration, conducted a study of underprivileged children and concluded that these students could not learn; the school systems would not be able to teach them (Lezotte, 2002). Some think that the crisis in education is just a fraud. Some parents feel that whatever is wrong with American education does not affect them because the school their children go to is doing just fine (Allexsaht-Snider & Hart, 2001; Finn, 1998a; NCEE, 1998).

The future of American society and individuals depends on a solid education. The young person without a solid education will not see a very bright future. NCEE (1998) states that: “a good education is the great equalizer of American society” (p. 3). “Good post-secondary education has become absolutely indispensable for economic success, both for individuals and for American society” (NCEE, 1998, p. 2). Currently, students are kept in school for a certain number of years and excellence is demanded from the elite, while accepting minimal performance from the majority of students. Some may believe that America can prosper with only the elite being well-educated, but the wasted human potential is unconscionable. Mediocre schooling affects the quality of our politics, culture, economy, and our communities (NCEE, 1998).

American schools are doing a poor job educating children, especially our disadvantaged and minority students (NCEE, 1998). Many times disadvantaged and minority children are left to learn on their own and are not given challenging mathematics. In a recent study in Texas, teachers’ literacy levels were more closely related to student achievement than any other aspect of teaching, which suggests that recruiting teachers that are more intelligent will do more for education than requiring all the teachers to go through pre-service training (Allexsaht-Snider & Hart, 2001; Thomas

B. Fordham Foundation, 1999).

The United States does have excellent schools available so the educators of this nation know how to create great schools, but still have not found the solution to ensure every student is educated and well-prepared to enter college at the appropriate academic level (Finn, 1998a; NCEE, 1998; Strawser & Miller, 2001). After James Coleman reported that children from poor socioeconomic backgrounds could not learn, Ron Edmonds took on the challenge to prove him wrong. Edmonds became the expert on high-poverty, high-performing schools (Brady, 2003). His findings are very specific on how to create great schools.

Mathematics Anxiety

Mathematics anxiety is related to poor performance in mathematics, and is a very common phenomenon among college and university students today (Goolsby et al., 1988; McLeod, 1992; Perry, 2004). Hembree (1990) found that a reduction of mathematics anxiety follows higher achievement, and that both mathematics and test anxiety relate to general anxiety. Ma (1999) found from a meta-analysis of 26 studies that higher mathematics achievement resulted in lower mathematics anxiety. Mathematics anxiety can range from a small amount of test anxiety (Hembree, 1990) to extreme anxiety, including physical symptoms such as being nauseous, and feelings of tension when manipulating numbers to solve mathematics problems (Alexander & Martray, 1989; Bessant, 1995; Bitner, Austin, & Wadlington, 1994; Perry, 2004; Woodard, 2004). Mathematics anxiety has been referred to as an illness that is emotional as well as a cognitive dread of mathematics (Fiore, 1999). Steven Krantz (1993) describes an extreme form of this syndrome: “Mathematics anxiety is an inability by an otherwise intelligent person to cope with quantification, and more generally, mathematics. Frequently the outward symptoms of mathematics anxiety are physiological rather than psychological. When confronted with a mathematics problem, the sufferer has sweaty palms, is nauseous, has heart palpitations, and experiences paralysis of thought …this quick description does not begin to describe the torment” (p. 22). Most college students do not have this level of anxiety, but many do suffer from mathematics anxiety in some form or other (Perry, 2004).

Underprepared mathematics students enter college knowing their deficiencies, but desire to work toward and achieve a college education (Gourney, 1992). The students bring with them years of failure, especially in mathematics. The students are afraid of mathematics and are convinced that success in a mathematics class is unattainable because of past failures. The students feel not being able to learn is their fault. Students who have been failures all their lives actually have been successful in one respect, to master mathematics failure (Kennedy, 1999). Students who have more experiences with academic failure tend to persist less and tend to give up more quickly when confronted with difficult mathematical tasks (Bitner et al., 1994; Gourney, 1992; Jones et al., 1997; Paravate et al., 1998). The condition of mathematics failure leads students, caught in the cycle of failure, to social promotion that bypasses the demonstration of mathematical mastery of the concepts appropriate for each grade level (NCEE, 1998). Also, students in high poverty schools are more likely to be taught by out-of-field teachers (National Commission on Teaching and America’s Future, 1996), and these students are less likely to complete a rigorous high school curriculum (National Center for Educational Statistics, 2001), leading them to college and universities underprepared.

Eventually, students who have experienced repeated failure reach a point in their secondary program, usually their senior year, when they opt out of taking any additional mathematics. These students will develop a less complete understanding of mathematics, and will be less likely to matriculate at a postsecondary institution (NCEE, 1998). Failure in mathematics classes at the high school level must not be the reason students give up on themselves and their future (Kennedy, 1999).

Some Suggestions for Overcoming Mathematics Anxiety

In 1989, the National Council of Teachers of Mathematics (NCTM) encouraged the use of calculators as an instructional aid and computational tool in the classroom. "Technology is essential in teaching and learning mathematics; it influences the mathematics that is taught and enhances students' learning" (NCTM, 2000). Acelajado (2001) found that the use of technology reduced anxiety in mathematics problem solving.

Goolsby et al.'s (1988) findings indicate that a student's confidence in their ability to learn mathematics was the only variable included, which contributed to prediction of performance in a developmental mathematics course. Students in developmental classes would benefit from a plan to increase confidence and lower the level of anxiety associated with mathematics. "An effective instructor in developmental mathematics must not limit the instructional process to concerns of cognition; it is imperative that instructors focus attention on both the affective and cognitive domains" (Goolsby et al., 1988, p. 18). One other suggestion for combating mathematics anxiety is to have a strong support system. On the college level, tutoring services are usually available as well as creating study groups with classmates (Schwartz, 2000). Teachers can build confidence by being available outside of classroom to help developmental students construct study skills, and helping students evaluate their progress. Classes can be offered to help students with study skills, goal setting, and anxiety reduction (Fiore, 1999; Goolsby et al., 1988). Finally, Norwood (1994) found that student's level of mathematics anxiety decreased in a more structured environment as compared to the less structured environment. Anxiety associated with mathematics can be lowered with affective strategies.

Fairbanks (1992) thought that students might learn more if they were not worried about passing so he came up with the contract method to treat mathematic anxiety. Fairbanks created a contract with specific goals that all students could meet. If the students met all requirements on the contract, they were guaranteed a passing grade of D for the course. The contract was strictly optional; the students could choose not to participate without penalty. Fairbanks found that the contract did relieve mathematics anxiety with a 95% passing rate, compared to a 75% passing rate for students who chose not to use the contract method. Fairbanks interviewed the students who had chosen the contract method and the students said that knowing they would pass the course relaxed them and they did far better than they had expected they would.

Attitude toward Mathematics

Beliefs, attitudes, and emotions are often considered the main components of affect (McLeod, 1992). In the early 1970s, an individual's attitude toward mathematics came to be one of the central topics in the affective domain of mathematics education; the Fennema-Sherman attitude scale (Fenneman-Sherman, 1976) represents this period. For students to succeed at remediation they need a positive attitude (Cornell, 1999; Fiore, 1999).

Some students placed in developmental mathematics courses in college do not have a chance to succeed due to a negative attitude with respect to mathematics or the fact that they feel inferior because they are in need of remediation (Hammerman, 2003). Students placed in a developmental mathematics class will need help overcoming their negative attitudes. Although the past cannot be changed, instructors of developmental students can help students overcome their past by encouraging a positive attitude and fresh outlook (Fiore, 1999; Hammerman, 2003).

Research using a constructivist approach has determined the effects on students' attitude toward mathematics. This study found that the constructivist approach helped students gain confidence in their ability to do mathematics and helped the students realize that it takes commitment. The students are responsible for their learning and were not afraid to take risks. The students became accountable for their mistakes (Acelajado, 2001).

Many students placed in a developmental mathematics class in college or a university do not have a chance at success due to a negative attitude or outlook with respect to mathematics or being placed in a remedial class (Hammerman, 2003). The main problem with attitude toward mathematics is that it often relates to a student's success or failure.

Reasons for Failure

Cornell (1999) identified several sources of frustration and failure as cited by graduate students taking a mathematics instruction seminar for certification in elementary education. Among the frustrations cited were (a) assumed student knowledge, (b) computational skills deemed easy by the instructor, (c) no sympathy for struggling students, (d) obscure mathematical vocabulary, (Cohen & Fowler, 1998; Cornell, 1999), (e) incomplete instruction, (f) skill and drill exercises, (g) rote memory, and (h) no real-world connection (Cornell, 1999). Cornell (1999) believed that students who were not able to keep up with the rest of the class suffered from compounded sources of frustration, which led to feelings of inadequacy and failure. The students interviewed by Cornell compared this particular frustration to a foot race. Cornell (1999) stated, "Once you fall behind it is impossible to catch up. Since mathematics is learning a concept and then building on that concept, it is essential that a student keeps up and does not fall behind because they will never catch up" (p. 3). The immediacy poses the best chances to circumvent feeling of frustration.

Mathematics vocabulary is another point of anxiety. Mathematics is difficult because it is a language in itself; therefore, educators must approach the learning of mathematics as if they are teaching a second language. Assessing a student's knowledge and then building on that knowledge has been recognized as a very important tool in the teaching of mathematics (Capraro, Kulm, & Capraro, 2001). Problems still exist because students are placed in remedial classes throughout their school experience; yet, they still enter college underprepared (Allexsaht-Snider & Hart, 2001; Cornell, 1999; Donlevy & Donlevy, 1997; Kennedy, 1999).

Goals and Philosophies of Developmental Education

The goal of remediation is to help students who have not mastered mathematical concepts to master the concepts. Many times these remedial classes do not accomplish the goal intended. The reason remedial classes do not work is because, by the time students are remediated, they have fallen so far behind they cannot catch up (Cornell, 1999). It was also found that programs offered to students labeled "at risk" lacked rigor (Donlevy & Donlevy, 1997). Less was expected from these students, so they gave less. The students lacked basic skills; therefore, their remediation dealt more with what they did not know than with encouraging problem solving skills. Donlevy and Donlevy (1997) stated, "Innovative applications or learning situations that draw on students' own experiences and cultures require higher-order problem solving, which these students are not ready for" (p. 7).

It was found that most of the students placed at risk for school failure were minority students who never had the opportunity to experience demanding mathematics and science. Once the students were identified as at risk, they were labeled "slow learners" or placed in a Chapter Title I program. No goals were set for these students except to make sure they were in some type of remedial class. The only goal was to slow down the pace and make the mathematics content easier. "Drill-and-Kill" with worksheet after worksheet was given to these students with no application in sight (Allexsaht-Snider & Hart, 2001; Cornell, 1999; Donlevy & Donlevy, 1997). Donlevy and Donlevy (1997) further found that the school district would “delegate the design, preparation, and selection of curriculum and instructional policies and materials to specialists in state departments of education, to central district offices, and to publishers in order to ensure remote control of classroom activities” (p. 7). Many times the programs these students are placed into cripple them in such a way that rigorous mathematics becomes impossible. The possibility of these ‘crippled’ students entering an elite college, or any college, or being able to seek career opportunities in science or mathematics or positions of authority in their communities becomes an unlikely scenario (Donlevy & Donlevy, 1997). Kennedy (1999) stated he becomes a little impatient with people who say that we need to keep standards high by weeding out the students who cannot do mathematics. Allexsaht-Snider and Hart (2001) explained an alternative to a weeding out philosophy of students. Allexsaht-Snider and Hart (2001) stated “ As a society, we need to move away from a view of mathematics as a sieve that filters out the less able and toward mathematics as a net that gathers more and more students” (p. 96). The American society needs to adopt the philosophy that mathematics is a net that gathers more students.

Teaching Developmental Students

The Institute of Higher Education Policy (1998) states that remediation is a core function of higher education. Remediation must look at all the needs of the student, including emotional needs as well as academic needs. Teaching and learning must be interactive. Teachers must know their students' needs and difficulties with mathematics so that the teacher can change their teaching strategies to meet the students' needs. To combat the anxiety associated with the learning of mathematics, teachers must work on their own attitudes, as well as the attitudes of their students. If a student does not understand what is being taught, then it is imperative to find a way to teach that student. Teachers should convey to the students that they believe in them and know that they can be successful as long as they do not give up (Adeeb, Bosnick, & Terrell, 1998; Black, 1998; Donlevy & Donlevy, 1997; Schwartz, 2000). Accelerated learning has been recommended for students who are remedial students (Adeeb et al., 1998; Black, 1998; Donlevy & Donlevy, 1997; Schwartz, 2000).

Teachers must change their beliefs about which students in their classroom have the ability to learn mathematics. Some teachers do believe that teachers and schools are the keys for student learning, while others believe that student learning is attributed to the students' own abilities and background experiences (Allexsaht-Snider & Hart, 2001). Students need to see clear precise examples that have meaning (Cornell, 1999; Schwartz, 2000). Revisiting previous concepts with students will allow the students to see mathematics as building blocks. Revisiting previous concepts approach can help students build a more positive attitude about learning mathematics and reduce anxiety associated with mathematics classes (Cornell, 1999; Schwartz, 2000).

NCTM stresses that communication and problem solving are important. Students will improve in these areas when allowed to practice them often and then demonstrate knowledge. A portfolio is a means of assessing a student's learning. Traditional testing does not allow a student to show what the student knows. A portfolio is one way of displaying knowledge.

Mathematics can be taught effectively if teachers remember the reason for teaching is to produce students who can logically think through complex situations in order to reach a sensible conclusion about the problems being solved. Problem solving is beneficial to the growth of the students in that the students will have to be problem solvers the rest of their lives. A teacher needs to know what knowledge the students possess. This knowledge can be learned through conversations with the student, observations, and the reading of pupils' work. The teacher must have a positive attitude. The teacher must not become frustrated with underprepared students (Adeeb et al., 1998; Allexsaht-Snider & Hart, 2001; Black, 1998; Cornell, 1999; Schwartz, 2000). To ensure the success of all students in mathematics, the teacher must view each student as potentially gifted, and full of curiosity and intelligence, and not see the student as developmental or remedial (Adeeb et al., 1998; Allexsaht-Snider & Hart, 2001, Donlevy & Donlevy, 1997). Resources are available to assist teachers to make mathematics fun and meaningful. Do not assume that your students know mathematical vocabulary and do not make students memorize mathematics ideas. Memorization is an indication that your students are not really understanding what you are teaching and may have gaps in their understanding. Instruction should have an element of diagnosis and remediation so that student errors can be addressed immediately (Cornell, 1999; Schwartz, 2000; Donlevy & Donlevy, 1997).

What works in remediation? Boylan and Saxon (1999) reported that mastery learning, some degree of structure, varying teaching methods, theory-based courses, centralized programs, mandatory assessment and placement, counseling, and tutoring were found to be best practices for students in need of remediation. Boylan and Saxon (1999) also discovered factors that contribute to the success of remediation, such as classroom/laboratory integration, institution-wide commitment, consistency of academic standards, learning communities and paired courses, supplemental instruction, strategic learning, professional training, student orientation, and critical thinking.

It is interesting to note that, although this body of knowledge has been available, it has not been widely used by practitioners. The author's observations from statewide studies of remedial education in Mississippi, South Carolina, North Carolina, and Texas suggest that fewer than half of the faculty teaching remedial courses are trained to do so or use the literature of the field to guide their practice. Providing effective remediation is not a mysterious proposition. We know how to do it. We simply do not use what we know (Boylan & Saxon, 1999).

Computer-based Instruction for Developmental Students

Research on the effects of computer-based instruction has been conducted in the past ten years. An analysis of 123 colleges and universities that used computer-based instruction revealed that the use of a computer as a tutor designed to supplement regular instruction had the following positive effects: (a) more student learning in less time, (b) slightly higher grades on posttests, and (c) improved student attitudes toward learning (Kulik & Kulik, 1986).

Studies

California State University at Bakersfield conducted a study on the effectiveness of using a Computer Algebra System (CAS) in a developmental algebra course. The students took an Entry Level Mathematics (ELM) test before enrolling in a course. Of the students who were tested, 87.5% were placed in a developmental class. The purpose of developmental mathematics is to raise the competency of the students taking those classes to that of the general population. According to the literature, regardless of the level of mathematics, using technology in the classroom improves mathematical understanding. It has also been found that technology improves students' problem-solving skills. The students went straight from DERIVE, a computer algebra system, to Introductory Statistics class. It was found that using a CAS in Intermediate Algebra has allowed the students to develop their mathematical skills by freeing them to focus on understanding the problems and doing mathematics. More importantly, the students have been able to transfer their new analytical skills into the statistics course and presumably into other courses as well (Shaw, Jean, & Peck, 1997).

Keup (1998) studied the use of technology in remedial education. The digest discusses two computer-aided instruction systems, SYNERGY and INVEST, used in remedial education. The results have been quiet positive. Researches found that the components of a successfully run computer-based remedial class include mature and independent students, a sophisticated computer system, and a well-equipped computer lab. The demand for developmental education at the postsecondary level continues to increase, and must be addressed at the community college level and on college and university campuses. It appears that technology can provide one answer to this growing challenge (Keup, 1998).

Math magic is another remedial teaching system designed for high school mathematics students. The main components of Math magic are very similar to ALEKS. Using computers for remedial teaching is useful and an appropriate use of computers in education, and has shown that providing an individualized and adaptive problem-solving session to students has improved their skills in mathematics. It has shown that this system improves the overall performance of students, and more importantly, helps weaker students more than above-average students (Paravate et al., 1998).

Assessment

NCTM (1989) has encouraged moving away from test taking that only exhibits the student's ability to do computational skills toward assessment that shows how a student can use the mathematical concepts they have learned in a practical way. Other forms of assessment should also be investigated. The students should be given many opportunities to show what they know in mathematics. Major tests still should focus on knowledge, but within that assessment a variety of test questions should be included, such as some straightforward and simple problems along with required writing, and some problems that require creative problem solving. Teachers should assess students in meaningful ways. Frequently, teachers find it difficult to create challenging assessments that allow students to experience mathematics successes (Cohen & Fowler, 1998; Kennedy, 1999; Lappan, 1999).

Asking questions on a mathematics test that assesses mathematics understanding goes far beyond mathematics. Assessment should be more than a piece of paper with the word "Test" written on the top of the page that the teacher gives at the end of some concept that is being taught. NCTM calls for assessment that includes dialogue between teacher and student. Students should be allowed to demonstrate the mathematical knowledge learned with manipulatives and to demonstrate why a procedure works. Pansy Waycaster (2001) conducted a study of college developmental mathematics courses and subsequent mathematics courses. The students were retested until mastery was achieved. This study showed that the students did not improve on the final exam, but their overall grade in the course did improve. Assessing students in a new way will require that we change our way of teaching. Mathematics teachers may or may not be up to the challenge of putting into place new ways of teaching and testing the students in American classrooms (Black, 1998; Cohen & Fowler, 1998; Cornell, 1999; Juhler, et al., 1998; Kennedy, 1999; Strawser & Miller, 2001; Steele & Arth, 1998). The assessment of "at risk" children is very superficial (Donlevy & Donlevy, 1997). Test anxiety is a real problem for students with mathematics difficulties. The teacher should give the students strategies for test taking (Schwartz, 2000).

CHAPTER III

METHODOLOGY

Researchers are now debating the issue of validity and reliability of scores on computer-administered tests. Researchers have relied on pencil and paper testing to collect data. With the proliferation of computer use, testing in order to collect data would naturally replace the paper and pencil method. Some concerns about computer use for testing deals with the validity and reliability of the test scores. Some of the advantages of online testing are supplying scores that are more precise, a multitude of data, and tremendous savings of time and money. Validity and reliability scores are not diminished; in fact, they improve. There is no longer a need for testing centers and people to administer the tests; as a result, a great deal of money is saved. Test takers can take exams on any computer that has internet service (Barak & Cohen, 2002; Choi & Tinkler, 2002; Galli, 2001; Nagliere, Drasgow, Schmit, Handler, Prifitera, Margolis, & Velasquez, 2002; Roos, 2001; Swan, 2004; Ware, Sinclair, Gandek, & Bjorner, 2005).

Sampling Strategy Participants

The participants in this study included 54 freshmen students (enrolled in Experimental courses using ALEKS) and 39 Control students (enrolled in traditional lecture courses) enrolled in Intermediate Algebra classes at three colleges and two universities. Multiple universities and colleges were asked to be apart of this study to ensure sufficient sample size. The 54 students in the Experimental group attended two different universities labeled lu and cc. The 39 students in the Control group attended three different colleges and were labeled bre, bry, and ntcc. Data were also collected from 29 students who completed the ALEKS program one, two, and three years ago. Students were judged as not being prepared to begin college level mathematics classes by various measures by performance on the Scholastic Assessment Test, the American College Assessment, the Texas Higher Education Assessment, and other entrance exams. Each college or university has identified these students using their own criteria shown in Appendix A.

Instrumentation

Students in the Experimental and Control groups were given the following tests on a pretest and posttest basis: (a) National Achievement Test, First Year Algebra Test (NATFYAT) (Webb & Hlavaty, 1962); shown in Appendix B, (b) Mathematics Anxiety Rating Scale (MARS), and (c) Mathematics Attitude Scales (MA). In addition, demographic data were collected from each student participant. The NATFYAT (Webb & Hlavaty, 1962) has 48 multiple-choice questions suitable for an Intermediate Algebra class. The MARS has 30 questions on a 5-point Likert Scale. The MA has 47 questions rated on a 5-point Likert Scale.

National Achievement Test, First Year Algebra Test

The National Achievement Test, First Year Algebra Test (NATFYAT) was administered to the Experimental (n = 54) and Control (n = 39) groups. In previous studies, the test's reliability was determined by means of the correlation between the chance halves and the Spearman-Brown formula, and was based on more than 500 scores in which odd and even items were used. In previous studies, the score reliability of NATFYAT Form A was .905 and Form B was .911. In the present study, the students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest at the end of the semester. In the present study, the internal consistency reliability for the NATFYAT pretest was .701. Reliability of the NATFYAT was .793. These are considered sufficient for further statistical analyses (Pallant, 2001).

Mathematics Anxiety Rating Scale

In previous studies, the coefficient alpha score reliability was .914 with a test re-test of .894 (Capraro, Capraro, & Henson, 2001). Suinn (1972) reported test retest reliability coefficient for the Mathematics Anxiety Rating Scale (MARS) was calculated from the scores of college students retested seven weeks later. The reliability coefficient of 0.78 compares quite favorably with reliabilities over relatively short periods of 0.78 and 0.68 for measures of social anxiety. Internal consistency reliability coefficient was found to be 0.97 (N = 397), confirming that the scores are highly reliable testing for mathematics anxiety within that study. In the present study, the condensed version of the original Mathematics Anxiety Rating Scale was administered to the Experimental group (n = 54) and the Control group (n =39). The MARS consisted of 30 questions on perceived anxiety of mathematics. The minimum possible points on this test were 30 indicating no anxiety, and maximum possible points of 150 indicating extreme anxiety. Cronbach's alpha for the present study was .930.

Mathematics Attitude

The Fennema-Sherman Mathematic Attitude test was given to the Experimental group (n = 54) and the Control group (n =39). The Mathematics Attitude (MA) scale consisted of 47 questions. The 47 questions are divided into four categories: (a) Confidence toward mathematics (MAC), (b) Usefulness of mathematics (MAU), (c) Teacher influence (MAT), and (d) Male dominance (MAM). The four categories test for positive and negative attitudes. The Mathematics Attitude scale is a Likert Scale testing for positive and negative attitudes. The positive questions are scored 5 to 1 and the negative questions are scored 1 to 5, with a possible score of 235 (all 47 questions), giving the most positive attitude results down to 47 (all 47 questions), indicating a very poor attitude towards mathematics. In previous studies, the coefficient alpha score reliability was 0.97. Relating the items to the variables supported content validity: confidence, anxiety, value, enjoyment, and motivation (Tapia & Marsh, 2004). A sample of 480 (246 boys and 234 girls) students in Grade 11 in the United Arab Emirates completed an Arabic version of the shortened form of the Fennema-Sherman Mathematics Attitude scales. A factor analysis of the intercorrelations of responses to 51 items indicated the same general factors as in the original study. Internal consistency estimates of the reliability of scores on the total scale and on each scale for the short form were acceptable, with coefficient alpha ranging from .72 to .89 (Alkhateeb, 2004). In the present study, the students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest near the end of the semester. In the present study, the internal consistency reliability for scores on the pretest Mathematics Attitude was .926, and .929 for scores on the posttest Mathematics Attitude. These are considered sufficient for further statistical analyses (Pallant, 2001).

Past Experimental Groups One, Two, and Three Years Ago

Students that had taken Intermediate Algebra using ALEKS one, two, and three years ago were given the algebra test (NATFYAT), Mathematics Anxiety Rating Scale, and Mathematics Attitude. These past students were also contacted for interviews (*n*=10). Interview questions for students who took Intermediate Algebra using ALEKS one, two, and three years ago were the following:

1. Describe your past experiences in mathematics classes prior to coming to LeTourneau University. In what types of classes or instruction have you learned the most mathematics?
2. What are your general thoughts on ALEKS?
3. What did you like about ALEKS?
4. What did you dislike about ALEKS?
5. What would you suggest to improve ALEKS?
6. Do you think ALEKS prepared you for subsequent mathematics classes?
7. Do you have any other experiences with online learning? How would you compare ALEKS with your other online teaching/learning experiences?

Variables

The independent variables in this study are gender, age, ethnicity, and mathematics courses taken in the past. The dependent variables are National Achievement Test, First Year Algebra Test (Webb & Hlavaty, 1962), Mathematics Anxiety Rating Scale, and Mathematics Attitude scales.

Administration

The three pretests, National Achievement Test, First Year Algebra Test (Webb & Hlavaty, 1962), Mathematics Anxiety Rating Scale (MARS), Mathematics Attitude (MA) scales, and demographic surveys were administered early in the Fall 2005 (September) semester. These instruments were administered via the web where students had the option of whether or not to participate. To ensure participation in this study, the researcher offered gift certificates for pizza. In addition, teachers offered extra points on a homework assignment, project, or test as deemed appropriate by the teacher, and the students chose to place their name in a drawing to win an IPOD or a $50 gift certificate from Wal-Mart (3 gift certificates in all), which were provided by the researcher. The students who chose not to participate were given the opportunity for extra points on a homework assignment, project, or test as well. The researcher was asked by two of the colleges to provide a flyer with instructions on how to access the online tests contained in Appendix C. The researcher printed 1,300 flyers and mailed them to the head of the mathematics department. These flyers were then distributed to each teacher who was teaching an Intermediate Algebra class for distribution to the students in their classes. The instructors at the other colleges accepted e-mail attachments of the flyers. By the end of the three-week window for data collecting, the researcher had 50 participants in the Control group. Another college was contacted and the researcher was allowed to take two classes down to the lab to take the three tests. Then the two groups continued through the semester with the respective methods for learning Intermediate Algebra, either ALEKS or the traditional lecture method. At the end of the Fall 2005 semester (mid November through December 7, 2005), the students in the traditional class as well as the students in a computerized-algebra program, responded to the posttest battery of assessments. The students were sent a flyer by e-mail to instruct them on test protocol. An e-mail address had been given by each student in the demographics survey. At the close of the semester, beginning before Thanksgiving through December 16, 2006, the response on the posttest for the Control group was small (n=31), so a decision was made to collect more data in the spring. After pretest and posttest in the spring, there was an additional eight participants, giving a total of (n=39) for the Control group.

Data Analysis

The two groups of scores being compared are independent samples. This study is a comparison of two sample means; therefore, MANOVA, to test mean differences across the two groups, will be performed to analyze the NATFYAT pretest and posttest of each student in the Control group and the computerized-algebra group to test whether statistically significant differences exist. The NATFYAT will be the dependent variable, as well as the MARS and MA. A separate regression analysis in the two groups will be used to determine the relationship between the NATFYAT and MARS, NATFYAT and MA, and demographics. Depending upon the conformity of the data, parametric or non-parametric analyses will be conducted to determine differences between the NATFYAT and MARS, NATFYAT and MA, and demographics. The findings will show if the success in mathematics is increased or decreased as a result of anxiety, attitude, gender, age, ethnicity, number of mathematics courses taken in the past, or degree plans.

Research Question I

Does a mastery learning perspective of remediation, where students are expected to learn all the objectives in an Intermediate Algebra class, make a difference in mathematics achievement? A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the algebra pretest and posttest given to the Experimental group only. A scatterplot was first examined to view the relationship between the algebra pretest and posttest. The relationship between algebra pretest and posttest was investigated using a Pearson *r* correlation coefficient. A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the National Achievement Test, First Year Algebra Test.

Research Question II

What differences exist between students using Assessment and Learning in Knowledge Spaces (ALEKS) compared to students who are taught Intermediate Algebra using a traditional lecture style?

The algebra pretest and posttest was administered to the Experimental (n = 54) and Control (n = 39) groups. The test is a National Achievement Test, First Year Algebra Test (NATFYAT) consisting of 48 questions that Intermediate Algebra students would encounter in a college course. A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the algebra pretest and posttest given to the Experimental and Control groups, and a scatterplot was examined. The relationship between algebra pretest and posttest was investigated using a Pearson *r* correlation coefficient. A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the National Achievement Test, First Year Algebra Test (NATFYAT).

The Mathematics Anxiety Rating Scale (MARS) test was administered to the Experimental group (n = 54) and the Control group (n =39). The MARS test consisted of 30 questions on perceived anxiety of mathematics students. A Pearson r correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MARS given to the Experimental group and Control group. A scatterplot was first examined to view the relationship between the pretest and posttest MARS. The relationship between pretest and posttest MARS was investigated using a Pearson r correlation coefficient. A paired-samples t-test was conducted to evaluate the impact of the intervention on students' scores on the MARS.

The Fennema-Sherman Mathematic Attitude (MA) test was given to the Experimental group (n = 54) and the Control group (n =39). The MA test consisted of 47 questions, which are divided into four categories: (a) Confidence toward mathematics (MAC), (b) Usefulness of mathematics (MAU), (c) Teacher influence (MAT), and (d) Male dominance (MAM). A Pearson r correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MA given to the Experimental group and Control group. A scatterplot was first examined to view the relationship between the pretest and posttest MA. A paired-samples t-test was conducted to evaluate the impact of the intervention on students' scores on the MA.

Research Question III

Are there differential mathematics effects for either group based on demographic factors such as gender, age, ethnicity, number of mathematics courses taken in the past, and degree plans?

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the algebra pretest and posttest by gender. A scatterplot was first examined to view the relationship between the algebra pretest and posttest. A Pearson *r* correlation was conducted to test differences between Female (n = 56) and Male (n = 37) students on Intermediate Algebra concepts on algebra pretest and posttest. An ANOVA on gain scores was conducted by gender. A Pearson *r* correlation was conducted to test differences between age groups. An ANOVA on gain scores was conducted to test differences between ethnicity Caucasian (n = 64), African American (n = 9), Hispanic (n =15), Other (n = 5) students on Intermediate Algebra concepts on the algebra pretest and posttest.

Research Question IV

Do differences emerge between the two groups of students in their perceived level of mathematics anxiety?

The Mathematics Anxiety Rating Scale (MARS) test was given to the Experimental group (n = 54) and the Control group (n =39). This test consists of 30 questions relating to the perceived anxiety of mathematics students when considering taking a mathematics test and calculating mathematical problems. A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MARS given to the Experimental group and Control group. A scatterplot was first examined to view the relationship between the pretest and posttest MARS. The relationship between the pretest and posttest MARS was investigated using a Pearson *r* correlation coefficient. A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the MARS. A MANOVA was conducted to test differences between Experimental (n = 54) and Control (n = 39) groups of students on the MARS pretest and posttest. A MANOVA is used for analyses when there are two or more dependent variables. In this case, the two dependent variables are MARS pretest and posttest. This test was designed to measure perceived anxiety associated with mathematics.

Research Question V

Is the student's attitude toward mathematics a factor in the student's inability to be successful in Intermediate Algebra?

The Fenneman-Sherman Mathematics Attitude (MA) test was administered to the Experimental group (n = 54) and the Control group (n =39). A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MA given to the Experimental group and the Control group. A scatterplot was first examined to view the relationship between the pretest and posttest MA. The relationship between pretest and posttest MA was investigated using a Pearson *r* correlation coefficient. A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the MA. A MANOVA was conducted to test differences between Control (n = 39) and Experimental (n = 54) students on pretest and posttest MA. In this case, the two dependent variables are MA pretest and posttest. A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the four components of the MA (MAC, MAT, MAU, and MAM). A MANOVA was conducted to test differences between Experimental (*n* = 54) and Control (*n* = 39) students on MA pretest and posttest divided into the 4 components: Confidence, Teacher, Usefulness, and Male Dominance. In this case, the dependent variables are MA pretest and posttest on all four components.

Research Question VI

Is there a differential performance between students who use ALEKS and Control group counterparts, and are there measurable differences one, two, and three years after completing the program?

A MANOVA was conducted to test differences between Past Experimental (*n* = 29) and Control (*n* = 39) students on the three tests, NATFYAT, MARS, and MA. An interview was conducted with students that had taken an Intermediate Algebra course using ALEKS. Appendix D contains the questions that were used for the interview.

CHAPTER IV

RESULTS

This chapter presents the results of the statistical analyses conducted on the data and answers the research questions identified in Chapter I. This study focused on the following research questions: (I) Does a mastery learning perspective of remediation, where students are expected to learn all the objectives in an Intermediate Algebra class, make a difference in mathematics achievement? (II) What differences exist between students using ALEKS compared to students who are taught Intermediate Algebra using a traditional lecture style? (III) Are there differential mathematics effects for either group based on demographic factors such as gender, age, ethnicity, number of mathematics courses taken in the past, and degree plans? (IV) Do differences emerge between the two groups of students in their perceived level of mathematics anxiety? (V) Is student's attitude toward mathematics a factor in student's inability to be successful in Intermediate Algebra? (VI) Is there differential performance between students who use ALEKS and Control group counterparts, and are there measurable differences one, two, and three years after completing the program?

Reliability

It is critical to select scales for research studies that yield reliable scores. One main concern is the scale's internal consistency (i.e., the degree to which the items that make up the scale are related). Are items all measuring the same underlying construct? A commonly used indicator of internal consistency is Cronbach's alpha (Pallant, 2001). "The higher the item-total correlations then the lower the Cronbach's alpha would be if the item were deleted. If the Cronbach's alpha score is lower if the item were deleted, then the item is considered a better item" (Zientek, 2006, p. 76). The following items 2, 14, 17, 22, 28, 33, 37, 44, 48 in algebra pretest; 1, 59, 11, 14, 29, 37, 45 in algebra posttest; 18, 19 in MARS pretest: 25, 29 in MARS posttest; and 6 and 36 in MA both tests did not function well. The correlation between the item and the total composite score and Cronbach's alpha if the item was deleted are reported for all items and for each subscale in Tables 1 through 6. In summary, the coefficient alpha score reliability for the algebra pretest was .701, algebra posttest was .793, MARS pretest was .905, MARS posttest was .930, MA pretest was .926, and MA posttest was .929.

Table 1

Reliability Diagnostics for Algebra Pretest

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
Algaq1	.327	.688
Algaq2	.015	.704
Algaq3	.224	.694
Algaq4	-.103	.709
Algaq5	.111	.701
Algaq6	.409	.683
Algaq7	.381	.684
Algaq8	.298	.690
Algaq9	.223	.694
Algaq10	.215	.695
Algaq11	.154	.698
Algaq12	.344	.688
Algaq13	.000	.701
Algaq14	.256	.692
Algaq15	.268	.693
Algaq16	.171	.697
Algaq17	.013	.705
Algaq18	.311	.689

Table 1 (continued)

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
Algaq19	.530	.676
Algaq20	.079	.701
Algaq21	.174	.697
Algaq22	-.043	.707
Algaq23	.166	.697
Algaq24	.113	.700
Algaq25	.304	.690
Algaq26	.203	.696
Algaq27	.102	.701
Algaq28	-.165	.713
Algaq29	.463	.679
Algaq30	.315	.690
Algaq31	.123	.699
Algaq32	.421	.683
Algaq33	.004	.707
Algaq34	.332	.688
Algaq35	.220	.695
Algaq36	-.042	.707
Algaq37	.071	.703
Algaq38	.124	.700
Algaq39	.182	.697
Algaq40	.288	.691
Algaq41	.079	.703
Algaq42	.308	.689
Algaq43	.062	.702
Algaq44	-.032	.709
Algaq45	.202	.696
Algaq46	.044	.704
Algaq47	.144	.699
Algaq48	-.001	.706

Note. Alpha for the total scores on the 93 participants on the 48 variables was .701.

Table 2

Reliability Diagnostics for Algebra Posttest

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
Algbq1	.034	.796
Algbq2	.235	.790
Algbq3	.216	.790
Algbq4	.270	.789
Algbq5	.001	.797
Algbq6	.178	.792
Algbq7	.297	.788
Algbq8	.145	.793
Algbq9	.047	.796
Algbq10	.162	.792
Algbq11	.059	.796
Algbq12	.187	.791
Algbq13	.134	.793
Algbq14	.057	.796
Algbq15	.193	.791
Algbq16	.364	.786
Algbq17	.250	.789
Algbq18	.258	.789
Algbq19	.346	.786
Algbq20	.248	.789
Algbq21	.204	.791
Algbq22	.285	.788
Algbq23	.230	.790
Algbq24	.368	.785
Algbq25	.269	.789
Algbq26	.310	.787
Algbq27	.446	.783
Algbq28	.188	.791
Algbq29	.072	.795
Algbq30	.315	.787
Algbq31	.405	.785
Algbq32	.304	.788
Algbq33	.343	.786
Algbq34	.311	.787
Algbq35	.404	.784
Algbq36	.299	.788
Algbq37	.004	.797
Algbq38	.223	.790
Algbq39	.391	.785

Table 2 (continued)

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
Algbq40	.292	.788
Algbq41	.231	.790
Algbq42	.353	.786
Algbq43	.285	.788
Algbq44	.287	.788
Algbq45	.075	.795
Algbq46	.321	.787
Algbq47	.335	.787
Algbq48	.443	.784

Note. Alpha for the total scores on the 93 participants on the 48 variables was .793.

Table 3

Reliability Diagnostics for Pretest Mathematics Anxiety Rating Scale

Variables	Corrected Item – Total *r*	Cronbach's Alpha if Item Deleted
1. Taking an examination (final) in a math course.	.445	.902
2. Thinking about an upcoming math test one week before.	.567	.900
3. Thinking about an upcoming math test one day before.	.609	.900
4. Thinking about an upcoming math test one hour before.	.680	.898
5. Thinking about an upcoming math test five minutes before.	.557	.900
6. Waiting to get a math test returned in which you expected to do well.	.499	.901
7. Receiving your final math grade in the mail.	.373	.904
8. Realizing that you have to take a certain number of math classes to fulfill the requirements in your major.	.584	.900
9. Being given a "pop" quiz in a math class.	.570	.900
10. Studying for a math test.	.535	.901
11. Taking the math section of a college entrance exam.	.559	.900
12. Taking an examination (quiz) in a math course.	.500	.901

Table 3 (continued)

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
13. Picking up the math textbook to begin working on a homework assignment.	.620	.900
14. Being given a homework assignment of many difficult problems, which is due the next class meeting.	.536	.901
15. Getting ready to study for a math test.	.219	.905
16. Dividing a five-digit number by a two-digit number in private with pencil and paper.	.626	.899
17. Adding up 976 + 777 on paper.	.268	.905
18. Reading a cash register receipt after you purchase.	-.252	.915
19. Figuring the sales tax on a purchase that costs more than $1.00.	.034	.911
20. Figuring out your monthly budget.	.454	.902
21. Being given a set of numerical problems involving addition to solve on paper.	.553	.901
22. Having someone watch you as you total up a column of figures.	.622	.899
23. Totaling up a dinner bill that you think overcharged you.	.567	.900
24. Being responsible for collecting dues for an organization and keeping track of the amount.	.520	.901
25. Studying for a driver's license test and memorizing the figures involved, such as the distances it takes to stop a car going at different speeds.	.377	.903
26. Totaling up the dues received and the expenses of a club you belong to.	.505	.901
27. Watching someone work with a calculator.	.369	.903
28. Being given a set of division problems to solve.	.654	.899
29. Being given a set of subtraction problems to solve.	.525	.901
30. Being given a set of multiplication problems to solve.	.588	.900

Note. Alpha for the total scores on the 92 participants on the 30 variables was .905.

Table 4

Reliability Diagnostics for Posttest Mathematics Anxiety Rating Scale

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
1. Taking an examination (final) in a math course.	.605	.927
2. Thinking about an upcoming math test one week before.	.581	.928
3. Thinking about an upcoming math test one day before.	.685	.926
4. Thinking about an upcoming math test one hour before.	.654	.927
5. Thinking about an upcoming math test five minutes before.	.529	.928
6. Waiting to get a math test returned in which you expected to do well.	.396	.930
7. Receiving your final math grade in the mail.	.510	.929
8. Realizing that you have to take a certain number of math classes to fulfill the requirements in your major.	.611	.927
9. Being given a "pop" quiz in a math class.	.663	.926
10. Studying for a math test.	.657	.927
11. Taking the math section of a college entrance exam.	.649	.927
12. Taking an examination (quiz) in a math course.	.745	.925
13. Picking up the math textbook to begin working on a homework assignment.	.660	.927
14. Being given a homework assignment of many difficult problems that is due the next class meeting.	.672	.926
15. Getting ready to study for a math test.	.759	.925
16. Dividing a five-digit number by a two-digit number in private with pencil and paper.	.609	.927
17. Adding up 976 + 777 on paper.	.309	.930
18. Reading a cash register receipt after you purchase.	.237	.931
19. Figuring the sales tax on a purchase that costs more than $1.00.	.363	.930
20. Figuring out your monthly budget.	.334	.930
21. Being given a set of numerical problems involving addition to solve on paper.	.530	.928
22. Having someone watch you as you total up a column of figures.	.669	.926
23. Totaling up a dinner bill that you think overcharged you.	.474	.929

Table 4 (continued)

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
24. Being responsible for collecting dues for an organization and keeping track of the amount.	.454	.929
25. Studying for a driver's license test and memorizing the figures involved, such as the distances it takes to stop a car going at different speeds.	.318	.931
26. Totaling up the dues received and the expenses of a club you belong to.	.454	.929
27. Watching someone work with a calculator.	.397	.930
28. Being given a set of division problems to solve.	.653	.927
29. Being given a set of subtraction problems to solve.	.409	.932
30. Being given a set of multiplication problems to solve.	.493	.929

Note. Alpha for the total scores on the 90 participants on the 30 variables was .930.

Table 5

Reliability Diagnostics for Pretest Mathematics Attitude

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
C1. I am sure that I can learn math.	.580	.923
T2. My teachers have been interested in my progress in math.	.318	.925
U3. Knowing math will help me earn a living.	.634	.923
C4. I don’t think I could do advanced math.	.538	.923
U5. Math will not be important to me in my life's work.	.409	.925
M6. Males are not naturally better than females in math.	-.085	.929
T7. Getting a teacher to take me seriously in math is a problem.	.231	.926

Table 5 (continued)

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
C8. Math is hard for me.	.400	.924
M9. It's hard to believe a female could be a genius in math.	.358	.925
U10. I'll need math for my future work.	.600	.923
M11. When a woman has to solve a math problem, she should ask a man for help.	.198	.926
C12. I am sure of myself when I do math.	.449	.924
U13. I don’t expect to use much math when I get out of school.	.593	.923
T14. I would talk to my math teachers about a career that uses math.	.471	.924
M15. Women can do just as well as men in math.	.182	.926
T16. It's hard to get math teachers to respect me.	.225	.926
U17. Math is a worthwhile, necessary subject.	.438	.924
M18. I would have more faith in the answer for a math problem solved by a man than a woman.	.285	.925
C19. I’m not the type to do well in math.	.590	.923
T20. My teachers have encouraged me to study more math.	.256	.926
U21. Taking math is a waste of time.	.674	.923
T22. I have a hard time getting teachers to talk seriously with me about math.	.294	.925
C23. Math has been my worst subject.	.598	.922
M24. Women who enjoy studying math are a little strange.	.464	.924
C25. I think I could handle more difficult math.	.578	.923
T26. My teachers think advanced math will be a waste of time for me.	.475	.924
U27. I will use math in many ways as an adult.	.626	.922
M28. Females are as good as males in geometry.	.341	.925
U29. I see math as something I won’t use very often when I get out of high school.	.659	.922
T30. I feel that math teachers ignore me when I try to talk about something serious.	.307	.925

Table 5 (continued)

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
M31. Women certainly are smart enough to do well in math.	.263	.925
C32. Most subjects I can handle OK, but I can't do a good job with math.	.679	.922
C33. I can get good grades in math.	.430	.924
U34. I'll need a good understanding of math for my future work.	.679	.922
T35. My teachers want me to take all the math I can.	.374	.925
M36. I would expect a woman mathematician to be a forceful type of woman.	-.063	.928
C37. I know I can do well in math.	.702	.922
M38. Studying math is just as good for women as for men.	.409	.924
U39. Doing well in math is not important for my future.	.505	.923
T40. My teachers would not take me seriously if I told them I was interested in a career in science and math.	.518	.923
C41. I am sure I could do advanced work in math.	.686	.921
U42. Math is not important for my life.	.590	.923
C43. I'm no good in math.	.643	.922
U44. I study math because I know how useful it is.	.479	.924
T45. Math teachers have made me feel I have the ability to go on in math.	.319	.925
M46. I would trust a female just as much as I would trust a male to solve important math problems.	.150	.926
T47. My teachers think I'm the kind of person who could do well in math.	.479	.924

Note. Alpha for the total scores on the 89 participants on the 47 variables was .926.

Table 6

Reliability Diagnostics for Posttest Mathematics Attitude

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
C1. I am sure that I can learn math.	.484	.928
T2. My teachers have been interested in my progress in math.	.357	.928
U3. Knowing math will help me earn a living.	.581	.927
C4. I don't think I could do advanced math.	.547	.927
U5. Math will not be important to me in my life's work.	.492	.927
M6. Males are not naturally better than females in math.	.155	.931
T7.Getting a teacher to take me seriously in math is a problem.	.309	.929
C8. Math is hard for me.	.440	.928
M9. It's hard to believe a female could be a genius in math.	.265	.929
U10. I'll need math for my future work.	.578	.927
M11. When a woman has to solve a math problem, she should ask a man for help.	.225	.929
C12. I am sure of myself when I do math.	.437	.928
U13.I don't expect to use much math when I get out of school.	.531	.927
T14. I would talk to my math teachers about a career that uses math.	.349	.929
M15. Women can do just as well as men in math.	.269	.929
T16. It's hard to get math teachers to respect me.	.309	.929
U17. Math is a worthwhile, necessary subject.	.436	.928
M18. I would have more faith in the answer for a math problem solved by a man than a woman.	.352	.928
C19. I'm not the type to do well in math.	.617	.926
T20. My teachers have encouraged me to study more math.	.326	.929
U21. Taking math is a waste of time.	.708	.926
T22. I have a hard time getting teachers to talk seriously with me about math.	.531	.927
C23. Math has been my worst subject.	.562	.927
M24. Women who enjoy studying math are a little strange.	.418	.928
C25. I think I could handle more difficult math.	.566	.927

Table 6 (continued)

Variables	Corrected Item - Total *r*	Cronbach's Alpha if Item Deleted
T26. My teachers think advanced math will be a waste of time for me.	.622	.926
U27. I will use math in many ways as an adult.	.624	.926
M28. Females are as good as males in geometry.	.349	.928
U29. I see math as something I won't use very often when I get out of high school.	.629	.926
T30. I feel that math teachers ignore me when I try to talk about something serious.	.453	.928
M31. Women certainly are smart enough to do well in math.	.346	.928
C32. Most subjects I can handle OK, but I can't do a good job with math.	.609	.926
C33. I can get good grades in math.	.430	.928
U34. I'll need a good understanding of math for my future work.	.589	.927
T35. My teachers want me to take all the math I can.	.256	.929
M36. I would expect a woman mathematician to be a forceful type of woman.	.198	.930
C37. I know I can do well in math.	.670	.926
M38. Studying math is just as good for women as for men.	.328	.929
U39. Doing well in math is not important for my future.	.399	.928
T40. My teachers would not take me seriously if I told them I was interested in a career in science and math.	.505	.927
C41. I am sure I could do advanced work in math.	.587	.926
U42. Math is not important for my life.	.546	.927
C43. I'm no good in math.	.663	.926
U44. I study math because I know how useful it is.	.525	.927
T45. Math teachers have made me feel I have the ability to go on in math.	.326	.929
M46. I would trust a female just as much as I would trust a male to solve important math problems.	.226	.929
T47. My teachers think I'm the kind of person who could do well in math.	.582	.927

Note. Alpha for the total scores on the 93 participants on the 47 variables was .929.

Factor Analysis

Factor analysis is not designed to determine whether one group is statistically significantly different from another group (Darlington, 2006; Pallant, 2001; Thompson, 2006). Factor analysis is a data reduction technique that takes a larger set of variables and reduces or summarizes them into a smaller set of factors. It is used to study patterns of relationships among many variables, discovering something about the nature of the variables (Darlington, 2006; Pallant, 2001).

Factor analysis answers four major questions: (a) How many different factors are needed to explain the pattern of relationships among these variables, (b) What is the nature of those factors, (c) How well do the hypothesized factors explain the observed data, and (d) How much purely random or unique variance does each observed variable include (Darlington, 2006). Statistical Packages for the Social Sciences (SPSS) was utilized for factor analyses conducted in the present study.

Factor Analysis of First Year Algebra Test

The 48 items of the National Achievement Test, First Year Algebra Test (NATFYAT) were subjected to principal component analysis (PCA). Before performing PCA, the eigenvalues of the correlation matrix were examined. The first eigenvalue was 4.548. The conclusion was that the 48 items tested for one factor: algebra concepts.

Factor Analysis of Mathematics Anxiety Rating Scale

The 30 items of the Mathematics Anxiety Rating Scale (MARS) were subjected to principal component analysis (PCA) with a varimax rotation. Before performing PCA, the suitability of data for factor analysis was assessed. Inspection of the correlation matrix revealed the presence of many coefficients of .3 and above. The Kaiser-Meyer-Oklin value was .803, exceeding the recommended value of .6 (Pallant, 2001) and the Bartlett's Test of Sphericity reached statistical significance, supporting the factorability of the correlation matrix. Principal component analysis revealed the presence of two components, explaining 31.10 percent and 14.57 percent of the variance for the pretest shown in Table 7, and explaining 34.927 percent and 12.642 percent of the variance for the posttest shown in Table 8. An inspection of the scree plot presented in Figure 1 revealed a clear break after the second component. The pattern/structure coefficients of the rotated solution presented in Tables 9 and 10 reveal the presence of simple structure (Thurstone, 1935), with both components showing a number of strong structure coefficients in components I and II. Therefore, two components were retained and labeled Mathematics Anxiety Pretest Studying (MAPRS) and Mathematics Anxiety Pretest Calculation (MAPRC).

Table 7

Explained Variance for the First Seven Eigenvalues on Pretest Mathematics Anxiety Rating Scale Prior to Rotation

Components	Total Explained Variance	Percent of Variance
1	9.330	31.100
2	4.371	14.569
3	1.780	5.937
4	1.638	5.460
5	1.379	4.597
6	1.146	3.821
7	1.057	3.523

Note. Eigenvalues greater than one were examined to determine the number of components to extract.

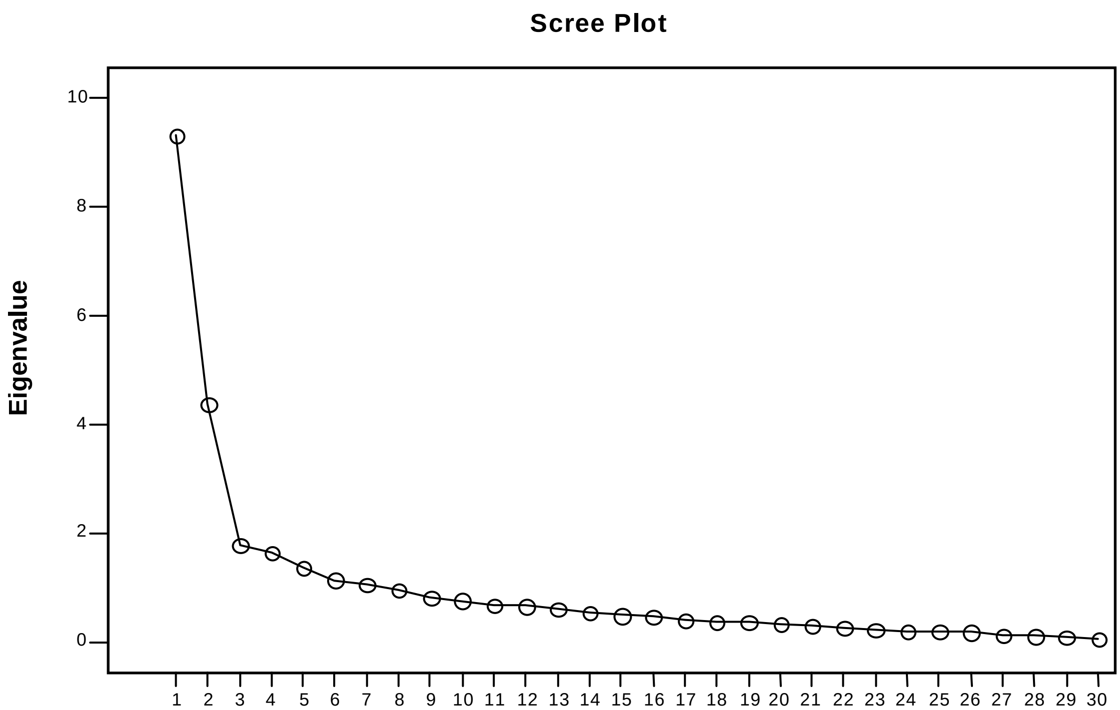

Figure 1. Sample Screeplot Results for the 93 Students on the MARS.

Table 8

Explained Variance for the First Seven Eigenvalues on Posttest Mathematics Anxiety Rating Scale Prior to Rotation

Components	Total Explained Variance	Percent of Variance
1	10.478	34.927
2	3.792	12.642
3	2.054	6.845
4	1.443	4.811
5	1.407	4.688
6	1.231	4.103
7	1.180	3.932

Note. Eigenvalues greater than one were examined to determine the number of components to extract.

Table 9

Sample Pattern/Structure Coefficients on Pretest Mathematics Anxiety Rating Scale

	Component		
Variables	I	II	h^2
S4. Thinking about an upcoming math test one hour before.	***.812***	.144	.681
S9. Being given a "pop" quiz in a math class.	***.783***	.031	.614
S12. Taking an examination (quiz) in a math course.	***.777***	-.071	.609
S3. Thinking about an upcoming math test one day before.	***.759***	.128	.593
S2. Thinking about an upcoming math test one week before.	***.751***	.094	.572
S1. Taking an examination (final) in a math course.	***.694***	-.041	.484
S14. Being given a homework assignment of many difficult problems, which is due the next class meeting.	***.687***	.100	.483
S5. Thinking about an upcoming math test five minutes before.	***.680***	.109	.474
S11. Taking the math section of a college entrance exam.	***.671***	.137	.469
S8. Realizing that you have to take a certain number of math classes to fulfill the requirements in your major.	***.635***	.231	.456
S10. Studying for a math test.	***.578***	.230	.388
S13. Picking up the math textbook to begin working on a homework assignment.	***.568***	.359	.451
S6. Waiting to get a math test returned in which you expected to do well.	***.518***	.219	.316
S7. Receiving your final math grade in the mail.	***.456***	.099	.218
S15.Getting ready to study for a math test.	.186	.128	.051
C19. Figuring the sales tax on a purchase that costs more than $1.00.	.080	-.034	.008
C26. Totaling up the dues received and the expenses of a club you belong to.	.034	***.809***	.655
C23. Totaling up a dinner bill that you think overcharged you.	.126	***.807***	.667
C30. Being given a set of multiplication problems to solve.	.198	***.765***	.625
C28. Being given a set of division problems to solve.	.315	***.714***	.610
C20. Figuring out your monthly budget.	.061	***.705***	.501
C21. Being given a set of numerical problems involving addition to solve on paper.	.201	***.689***	.519
C24. Being responsible for collecting dues for an organization and keeping track of the amount.	.160	***.689***	.500
C27. Watching someone work with a calculator.	.008	***.641***	.411
C25. Studying for a driver's license test and memorizing the figures involved, such as the distances it takes to stop a car going at different speeds.	.023	***.635***	.403

Table 9 (continued)

Variables	Component I	II	H^2
C17. Adding up 976 + 777 on paper.	-.091	***.629***	.404
C16. Dividing a five-digit number by a two-digit number in private with pencil and paper.	.391	***.566***	.473
C29. Being given a set of subtraction problems to solve.	.300	***.544***	.386
C22. Having someone watch you as you total up a column of figures.	.400	***.539***	.451
C18. Reading a cash register receipt after you purchase.	.048	***-.476***	.229

Note. N equals 93 and pattern/structure coefficients larger than .40 are bolded and italicized.

Table 10

Sample Pattern/Structure Coefficients on Posttest Mathematics Anxiety Rating Scale

Variables	Component I	II	h^2
S12. Taking an examination (quiz) in a math course.	***.830***	.186	.724
S1. Taking an examination (final) in a math course.	***.804***	-.010	.646
S11. Taking the math section of a college entrance exam.	***.766***	.109	.599
S5. Thinking about an upcoming math test five minutes before.	***.762***	-.084	.588
S9. Being given a "pop" quiz in a math class.	***.732***	.181	.568
S4. Thinking about an upcoming math test one hour before.	***.731***	.159	.560
S3. Thinking about an upcoming math test one day before.	***.724*** ***.230***	.577	
S2. Thinking about an upcoming math test one week before.	***.709***	.074	.508
S15. Getting ready to study for a math test.	***.699***	.386	.637
S10. Studying for a math test.	***.686***	.242	.530
S7. Receiving your final math grade in the mail.	***.685***	-.021	.469
S14. Being given a homework assignment of many difficult problems, which is due the next class meeting.	***.681***	.277	.541

Table 10 (continued)

Variables	Component		
	I	II	h^2
S8. Realizing that you have to take a certain number of math classes to fulfill the requirements in your major.	***.674***	.174	.485
S13. Picking up the math textbook to begin working on a homework assignment.	***.546***	.454	.504
C22. Having someone watch you as you total up a column of figures.	***.542***	.461	.507
S6. Waiting to get a math test returned in which you expected to do well.	***.476***	.070	.231
C21. Being given a set of numerical problems involving addition to solve on paper.	.212	***.681***	.509
C27. Watching someone work with a calculator.	.074	***.653***	.431
C23. Totaling up a dinner bill that you think overcharged you.	.174	***.647***	.449
C26. Totaling up the dues received and the expenses of a club you belong to.	.152	***.631***	.422
C18. Reading a cash register receipt after you purchase.	.111	***.624***	.401
C17. Adding up 976 + 777 on paper.	.040	***.620***	.386
C19. Figuring the sales tax on a purchase that costs more than $1.00.	.036	***.617***	.383
C16. Dividing a five-digit number by a two-digit number in private with pencil and paper.	.352	***.611***	.497
C29. Being given a set of subtraction problems to solve.	.137	***.606***	.386
C30. Being given a set of multiplication problems to solve.	.238	***.593***	.408
C20. Figuring out your monthly budget.	.021	***.590***	.349
C28. Being given a set of division problems to solve.	.510	***.447***	.558
C24. Being responsible for collecting dues for an organization and keeping track of the amount.	.292	***.450***	.288
C25. Studying for a driver's license test and memorizing the figures involved, such as the distances it takes to stop a car going at different speeds.	.119	***.405***	.178

Note. *N* equals 93 and pattern/structure coefficients larger than .40 are bolded and italicized.

Factor Analysis of Mathematics Attitude

The 47 items of the Mathematics Attitude (MA) were subjected to principal component analysis (PCA) with an oblique rotation. An oblique rotation was conducted because the factors did not appear to be orthogonal. (The type of oblique rotation used was Oblimin.) For example, the teacher may influence a student's attitude toward the usefulness of mathematics. In addition, the teacher and the student's perceived usefulness of mathematics, as well as any other combinations of effects, may affect a student's confidence. Before performing the PCA, suitability of data for factor analysis was assessed. Inspection of the correlation matrix revealed the presence of many coefficients of .3 and above. The Kaiser-Meyer-Oklin value was .737, exceeding the recommended value of .6 (Pallant, 2001), and the Bartlett's Test of Sphericity reached statistical significance, supporting the factorability of the correlation matrix.

An inspection of the scree plot shown in Figure 2 revealed a clear break after the fourth component. Principal component analysis revealed the presence of four components, explaining 29.93, 9.90, 7.10, and 5.41 percent of the variance shown in Table 11, and explaining 25.93,11.15, 7.12, and 5.583 percent of the variance shown in Table 12. The rotated solution, as shown in Tables 13 and 14, revealed the presence of simple structure (Thurstone, 1935), with all factors showing a number of strong structure coefficients in components 1, 2, 3, and 4. The four components have been labeled Mathematics Attitude pretest Confidence (MAPREC), Mathematics Attitude pretest Teacher (MAPRET), Mathematics Attitude pretest Usefulness (MAPREU), and Mathematics Attitude pretest Male Dominance (MAPREM).

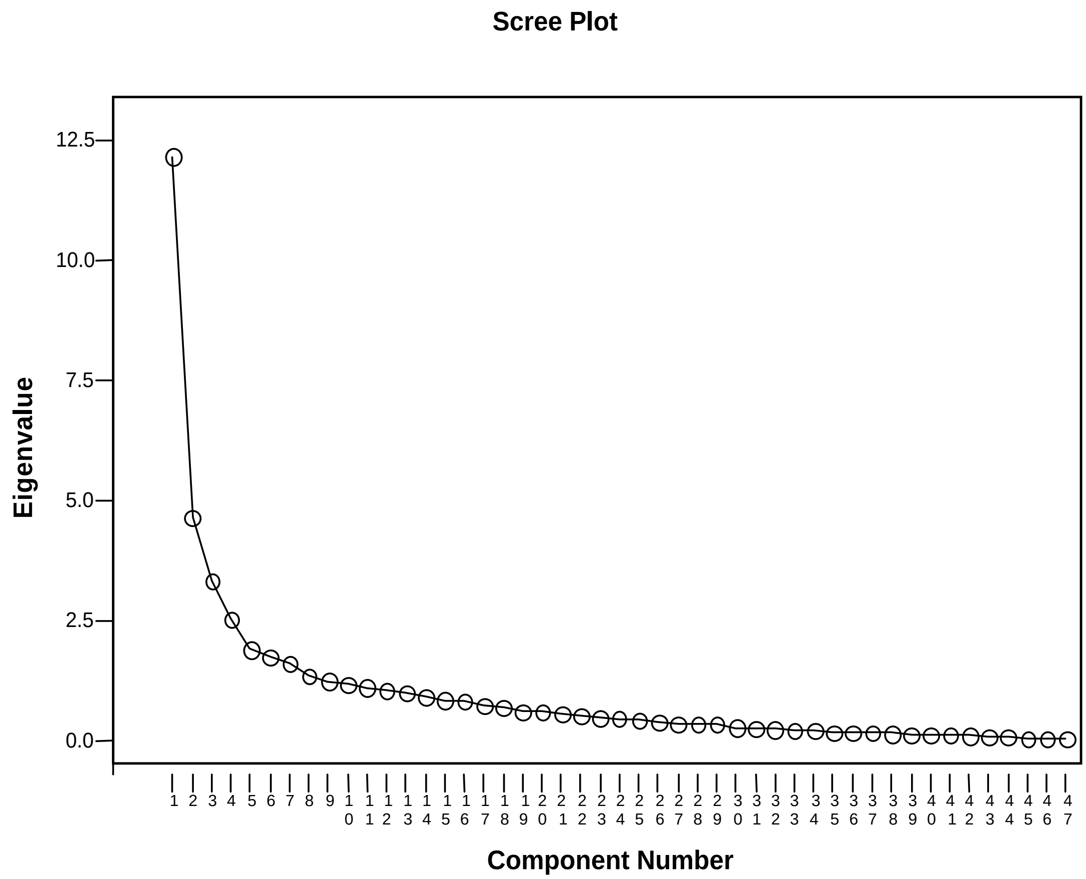

Figure 2. Sample Screeplot Results for the 93 students on the MA.

Table 11

Explained Variance for the First Seven Eigenvalues on Pretest Mathematics Attitude Prior to Rotation

Components	Total Explained Variance	Percent of Variance
1	12.789	29.934
2	4.655	9.904
3	3.338	7.103
4	2.542	5.409
5	1.913	4.069
6	1.746	3.714
7	1.641	3.492

Note. Eigenvalues greater than one were examined to determine the number of components to extract.

Table 12

Explained Variance for the First Seven Eigenvalues on Posttest Mathematics Attitude Prior to Rotation

Components	Total Explained Variance	Percent of Variance
1	12.185	25.925
2	5.241	11.151
3	3.348	7.123
4	2.624	5.583
5	1.921	4.087
6	1.633	3.475
7	1.506	3.205

Note. Eigenvalues greater than one were examined to determine the number of components to extract.

Table 13

Sample Pattern/Structure Coefficients on Pretest Mathematics Attitude

Variables	Factor I	Factor II	Factor III	Factor IV	h^2
U34. I'll need a good understanding of math for my future work.	***.848***	-.020	.437	.179	.763
U3. Knowing math will help me earn a living.	***.832***	.132	.272	.203	.693
U10. I'll need math for my future work.	***.829***	-.023	.352	.107	.721
U29. I see math as something I won’t use very often when I get out of high school.	***.788***	.225	.304	.276	.640
U21. Taking math is a waste of time.	***.767***	.156	.375	.304	.616
U27. I will use math in many ways as an adult.	***.766***	.201	.403	-.013	.679
U13. I don’t expect to use much math when I get out of school.	***.763***	.317	.208	.139	.641
U17. Math is a worthwhile, necessary subject.	***.682***	.030	.080	.251	.502
U42. Math is not important for my life.	***.613***	.325	.278	.308	.458
C37. I know I can do well in math.	***.579***	.242	.564	.400	.567
U39. Doing well in math is not important for my future.	***.565***	.309	.171	.291	.391
U5. Math will not be important to me in my life's work.	***.565***	.129	.186	.096	.326
U44. I study math because I know how useful it is.	***.531***	-.087	.395	.175	.360
T14. I would talk to my math teachers about a career that uses math.	***.500***	-.171	.364	.354	.410
T35. My teachers want me to take all the math I can.	***.458***	-.058	.230	.229	.245
T40. My teachers would not take me seriously if I told them I was interested in a career in science and math.	***.435***	.236	.334	.404	.337
M28. Females are as good as males in geometry.	.203	***.725***	.124	.055	.548
M15. Women can do just as well as men in math.	.022	***.698***	.004	.033	.494
M24. Women who enjoy studying math are a little strange.	.197	***.684***	.291	.276	.563
M11. When a woman has to solve a math problem, she should ask a man for help.	.041	***.680***	.060	-.008	.476
M31. Women certainly are smart enough to do well in math.	.170	***.655***	.003	.194	.447

Table 13 (continued)

Variables	Factor I	II	III	IV	h^2
M46. I would trust a female just as much as I would trust a male to solve important math problems.	.161	***.614***	-.204	.185	.466
M18. I would have more faith in the answer for a math problem solved by a man than a woman.	.133	***.605***	.048	.319	.423
M9. It's hard to believe a female could be a genius in math.	.141	***.573***	.246	.162	.383
M38. Studying math is just as good for women as for men.	.354	***.542***	.120	.246	.387
C32. Most subjects I can handle OK, but I can't do a good job with math.	.368	.165	***.855***	.172	.754
C43. I'm no good in math.	.366	.181	***.843***	.074	.742
C19. I'm not the type to do well in math.	.323	.146	***.814***	.084	.679
C23. Math has been my worst subject.	.308	.152	***.813***	.082	.678
C8. Math is hard for me.	.170	-.143	***.756***	.017	.608
C41. I am sure I could do advanced work in math.	.518	.171	***.747***	.171	.649
C25. I think I could handle more difficult math.	.441	-.044	***.703***	.703	.552
C1. I am sure that I can learn math.	.432	-.016	***.677***	.245	.524
C4. I don't think I could do advanced math.	.307	.073	***.672***	.262	.486
C12. I am sure of myself when I do math.	.317	-.105	***.601***	.158	.401
C33. I can get good grades in math.	.354	.063	***.506***	.171	.298
T47. My teachers think I'm the kind of person who could do well in math.	.356	-.198	***.491***	.446	.482
T45. Math teachers have made me feel I have the ability to go on in math.	.048	-.009	***.435***	.413	.361
M36. I would expect a woman mathematician to be a forceful type of woman.	.008	-.023	-.235	.214	.119
M6. Males are not naturally better than females in math.	-.04	-.030	-.160	.038	.030
T2. My teachers have been interested in my progress in math.	.207	.109	.076	***.695***	.484
T16. It's hard to get math teachers to respect me.	.183	.147	-.120	***.686***	.522
T30. I feel that math teachers ignore me when I try to talk about something serious.	.029	.307	.170	***.652***	.525

Table 13 (continued)

Variables	Factor I	II	III	IV	h^2
T26. My teachers think advanced math will be a waste of time for me.	.307	.141	.319	***.584***	.412
T22. I have a hard time getting teachers to talk seriously with me about math.	.205	.333	.007	***.545***	.375
T7. Getting a teacher to take me seriously in math is a problem.	.136	.247	-.014	***.518***	.308
T20. My teachers have encouraged me to study more math.	.229	-.059	.144	***.403***	.198

Note. *N* equals 93 and pattern/structure coefficients larger than .40 are bolded and italicized.

Table 14

Sample Pattern/Structure Coefficients on Posttest Mathematics Attitude

Variables	Factor I	II	III	IV	h^2
C43. I'm no good in math.	***.821***	.137	.322	-.289	.705
C8. Math is hard for me.	***.810***	-.207	.050	-.191	.713
C41. I am sure I could do advanced work in math.	***.787***	.098	-.004	-.384	.690
C32. Most subjects I can handle OK, but I can't do a good job with math.	***.775***	.041	.285	-.326	.616
C19. I'm not the type to do well in math.	***.766***	.075	.262	-.338	.602
C37. I know I can do math well.	***.743***	.072	.238	-.484	.616
T47. My teachers think I'm the kind of person who could do well in math.	***.739***	-.036	.424	-.202	.624
C12. I am sure of myself when I do math.	***.732***	.052	.090	-.075	.586
C25. I thin k I could handle more difficult math.	***.725***	.010	.157	-.377	.546
C1. I am sure that I can learn math.	***.569***	.152	.262	-.222	.357

Table 14 (continued)

	Factor				
Variables	I	II	III	IV	h^2
T45. Math teachers have made me feel I have the ability to go on in math.	***.532***	-.198	.300	-.071	.380
T14. I would talk to my math teachers about a career that uses math.	***.521***	-.103	-.147	-.383	.419
C33. I can get good grades in math.	***.467***	.142	.017	-.398	.309
T20. My teachers have encouraged me to study more math.	***.435***	.236	.334	.404	.385
T35. My teachers want me to take all the math I can.	.346	-.249	.214	-.225	.246
M28. Females are as good as males in geometry.	.123	***.766***	-.020	-.221	.644
M11. When a woman has to solve a math problem, she should ask a man for help.	-.110	***.744***	.205	-.104	.577
M46. I would trust a female just as much as I would trust a male to solve important math problems.	-.039	***.736***	.060	-.094	.551
M18. I would have more faith in the answer for a math problem solved by a man than a woman.	.114	***.703***	.206	-.144	.512
M15. Women can do just as well as men in math.	.010	***.665***	.207	-.087	.453
M24. Women who enjoy studying math are a little strange.	.108	***.652***	.232	-.320	.468
M31. Women certainly are smart enough to do well in math.	.076	***.611***	.203	-.242	.392
M9. It’s hard to believe a female could be a genius in math.	.050	***.582***	.135	-.119	.341
M38. Studying math is just as good for women as for men.	.099	***.500***	.122	-.303	.291
M36. I would expect a woman mathematician to be a forceful type of woman.	-.008	.318	.194	-.190	.138
T30. I feel that math teachers ignore me when I try to talk about something serious.	.205	.185	***.826***	-.185	.686
T22. I have a hard time getting teachers to talk seriously with me about math.	.234	.319	***.825***	-.273	.721

Table 14 (continued)

Variables	Factor I	II	III	IV	h^2
T26. My teachers think advanced math will be a waste of time for me.	.436	.131	***.709***	-.417	.637
T16. It's hard to get math teachers to respect me.	.130	.135	***.683***	-.109	.468
T7. Getting a teacher to take me seriously in math is a problem.	.046	.387	***.670***	-.059	.533
T40. My teachers would not take me seriously if I told them I was interested in a career in science and math.	.385	.075	***.602***	-.316	.454
T2. My teachers have been interested in my progress in math.	.422	.130	***.498***	.058	.420
U10. I'll need math for my future work.	.308	.232	.109	***-.820***	.678
U44. I study math because I know how useful it is.	.282	.093	.077	***-.814***	.672
U34. I'll need a good understanding of math for my future work.	.470	.104	-.012	***-.795***	.713
U13. I don't expect to use much math when I get out of school.	.275	.175	.161	***-.761***	.581
U29. I see math as something I won't use very often when I get out of high school.	.258	.368	.351	***-.742***	.639
U27. I will use math in many ways as an adult.	.398	.204	.198	***-.732***	.567
U21. Taking math is a waste of time.	.439	.309	.423	***-.664***	.593
U3. Knowing math will help me earn a living.	.364	.286	.264	***-.607***	.440
U17. Math is a worthwhile, necessary subject.	.179	.209	.257	***-.564***	.353
U5. Math will not be important to me in my life's work.	.270	.297	.209	***-.535***	.339
U42. Math is not important for my life.	.205	.318	.501	***-.527***	.479
U39. Doing well in math is not important for my future.	.162	.190	.344	***-.431***	.269
M6. Males are not naturally better than females in math.	.083	-.018	-.066	-.323	.123

Note. *N* equals 93 and pattern/structure coefficients larger than .40 are bolded and italicized.

Substantive Analyses

A Multivariate Analysis of Variance (MANOVA) was used to see the main and interaction effects of categorical variables on multiple dependent interval variables. One important use of MANOVAs is the ability to limit the probability of making experiment-wise Type I errors (Thompson, 2006). In addition, “multivariate methods best honor the reality to which the researcher is purportedly trying to generalize” (Thompson, 2006, p. 12). Like analysis of variance (ANOVA), MANOVAs use one or more categorical independent variables as predictors, but unlike ANOVA, there is more than one dependent variable. Where ANOVA tests the differences in means of the interval dependent for various categories of the independent(s), MANOVA tests the differences in the means of the multiple intervally-scaled dependents, for various categories of the independent(s) (Garson, 2001; Pallant, 2001; Van Den Bercken & Voeten, 2003). Planned comparison or post hoc comparisons, were performed to see which values of a factor contribute most to the explanation of the dependent. There are multiple potential purposes for MANOVA: (a) to compare groups formed by categorical independent variables on group differences in a set of interval dependent variables, (b) to use lack of difference for a set of dependent variables as a criterion for reducing a set of independent variables to a smaller, more easily modeled number of variables, and (c) to identify the independent variables that differentiate a set of dependent variables the most (Garson, 2001). Multivariate effect sizes were reported as partial η^2 and were found by computing 1- Wilks’ lambda. An a level of .05 was set as significant for all main effect analyses. For ANOVAs, post hoc analyses were performed using multiple univariate F tests, adjusting family wise a with the Bonferroni correction (0.05/4 = 0.0125).

All instruments (NATFYAT, MARS, and MA) were scored using Blackboard and entered into the SPSS software. Multiple universities and colleges were asked to be apart of this study to ensure sufficient sample size. The 54 students in the Experimental group attended two different universities labeled lu and cc. The 39 students in the Control group attended three different colleges and were labeled bre, bry, and ntcc. Descriptive statistics were calculated for all variables. The research design was a single 2 x 2 (sex: male or female x educational treatment: computer algebra system or lecture method) MANOVA and a single one-way (one categorical, independent variable: educational treatment, gender, age, or ethnicity) MANOVA based on the Wilks λ statistic. To determine if differences existed between Experimental and Control groups of students on their algebra achievement, mathematics anxiety, and mathematics attitude, MANOVAs and ANOVAs were conducted.

An independent-samples *t*-test is used when researchers want to compare the mean score on some continuous variable for two different groups, and a paired-samples *t*-test is used when a researcher wants to compare the mean scores for the same group of people on two different occasions, or matched pairs (Pallant, 2001). One categorical, independent variable and one continuous dependent variable are needed for the independent-sample *t*-test. The paired-samples *t*-test needs one categorical, independent variable (such as a test given at two different times), and one continuous, dependent variable measured on two different occasions (scores on the test given at two different times) (Pallant, 2001). An effect size must be calculated because statistical significance does not tell the magnitude of the intervention effects. One method is to calculate the Cohen's *d* statistic using the formula $d = (X_1 - X_2)/s$ where s is defined as the pooled estimate of the population variance (Hinkle, Wiersma, & Jurs, 2003; Thalheimer & Cook, 2002).

Research Question I

Does a mastery learning perspective of remediation, where students are expected to learn all the objectives in an Intermediate Algebra class, make a difference in mathematics achievement?

ALEKS is an internet based computer algebra system that is self-paced and provides immediate feedback. The student is given an assessment at the beginning of the semester and placed where the student is ready to learn. The students are expected to master 160 objectives in 15 weeks. Students in both schools were assigned to this class because of scores made on the SAT.

The algebra test was given to the Experimental group ($n = 54$). The test is a National Achievement Test, First Year Algebra Test consisting of 48 questions that Intermediate Algebra students would encounter in a college course. The students were given the test in September and again in December. The intervention (ALEKS) began as soon as the pretest was completed. The students were given the posttest at the end of the semester in December.

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the algebra pretest and posttest given to the Experimental group only. A scatterplot was first examined to view the relationship between the pretest and posttest algebra test as shown in Figure 3. A positive correlation can be seen in the scatterplot. The relationship between the algebra pretest and posttest was investigated using a Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables ($r = .411$, $n = 54$, $p = .002$) with higher scores on the pretest associated with higher scores on the posttest.

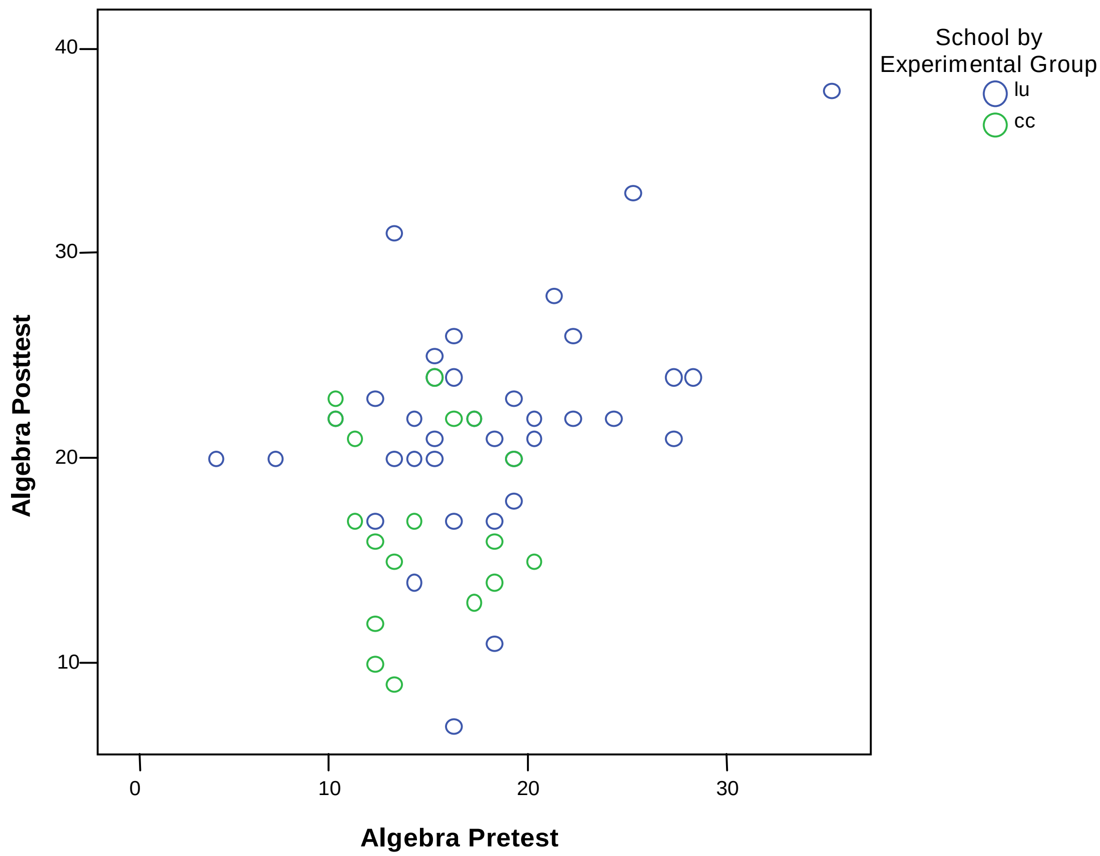

Figure 3. Scatterplot of Algebra Pretest as Independent Variable and Algebra Posttest as Dependent Variable of Experimental Group Only.

A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the National Achievement Test, First Year Algebra Test (NATFYAT). There was a statistically significant difference on algebra achievement from pretest (*M* = 16.56, S*D* = 5.493) to posttest (*M* = 20.56, S*D* = 5.67) as seen in Tables 15 and 16 (*t*(53) = -4.490, *p* = .0001). Although the results show differences in the two sets of scores and those differences were statistically significant, an effect size needs to be computed to determine the magnitude of the intervention. The effect size, Cohen's *d*, was .611.

Table 15

Descriptive Statistics for Algebra Pretest and Posttest for Experimental Group Only

Measure	Mean	*n*	SD	SEM
Algebra Pretest	16.56	54	5.493	.748
Algebra Posttest	20.26	54	6.674	.772

Table 16

Paired t-Test for Algebra Pretest and Posttest for Experimental Group Only

								95% Confidence Interval for Difference	
Variables	*n*	Mean	SD	SE	*t*	df	Sig (2-tailed)	Lower	Upper
Pretest Posttest	54	-3.7	6.061	.825	-4.490	53	.0001	-5.36	-2.05

Research Question II

What differences exist between students using Assessment and Learning in

Knowledge Spaces (ALEKS) compared to students who are taught Intermediate Algebra using a traditional lecture style?

Students enrolled in Intermediate Algebra classes were both given pretest and posttest algebra, Mathematics Anxiety Rating Scale, and Mathematics Attitude tests. The two groups of students were either enrolled in a course that used computer-generated instruction (n = 54) or lecture (n = 39).

Differences Between Groups on Algebra Test

The algebra test was administered to the Experimental (n = 54) and Control (n = 39) groups. The test is a National Achievement Test, First Year Algebra Test (NATFYAT), consisting of 48 questions that Intermediate Algebra students would encounter in a college course. The students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest at the end of the semester.

A Pearson r correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest algebra test given to the Experimental and Control groups. Figure 4 appears to show a positive relationship between pretest and posttest scores. The relationship between the algebra pretest and posttest was investigated using a Pearson r correlation coefficient. There was a medium positive correlation between the two variables for the Experimental group (r = .411, n =54, p = .002) and a smaller correlation for the Control group (r = .203, n = 39, p = .213). Groups with higher scores on the pretest associated with higher scores on the posttest.

A paired-samples *t*-test was conducted to evaluate the impact of the intervention on student scores on the National Achievement Test, First Year Algebra Test (NAFYAT). Descriptive statistics are presented in Table 17. There was a statistically significant

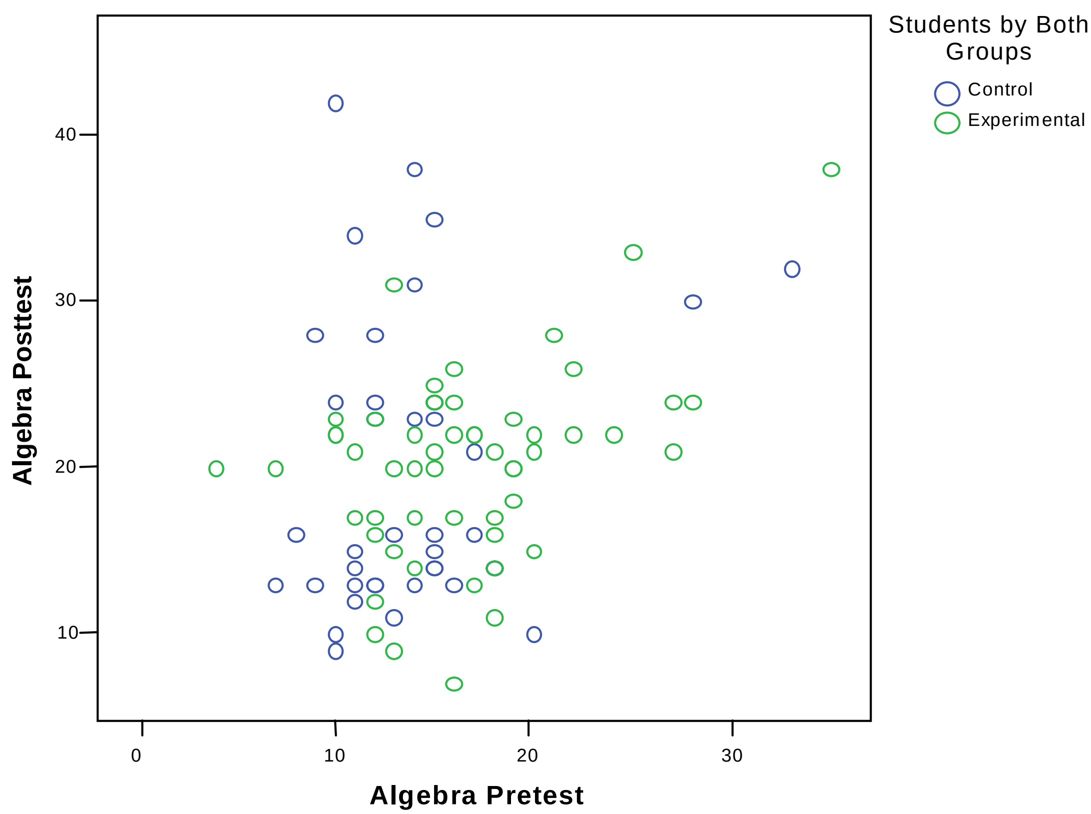

Figure 4. Scatterplot of Both Groups on Algebra Pretest and Posttest.

difference on algebra achievement for the Experimental group from the pretest (*M* = 16.56, S*D*= 5.493) to the posttest (*M* = 20.56, S*D* = 5.674), as shown in Tables 17 and 18 (*t* (53) = -4.490, *p* = .0001). There was also a statistically significant difference on the algebra achievement for the Control group from the pretest (*M* = 13.89, *SD* = 5.493) to the posttest (*M* = 19.67, S*D* = 6.674), also shown in Tables 17 and 18 (*t* (38) = -3.955, *p*

= .0001). There was also a statistically significant difference on the algebra achievement for both groups combined from the pretest (*M* = 15.44, S*D* = 5.396) to the posttest (*M* = 20.01, S*D* = 7.080), as shown in Tables 17 and 18 (*t* (92) = -5.864, *p* = .0001). The effect size statistic Cohen's *d* = .611 for the Experimental group and Cohen's *d* = .633 for the Control group, as well as both groups together Cohen's *d* = .608. Boxplots for the pretest and the posttest algebra for Experimental and Control groups are presented in Figures 5 and 6, respectively.

Table 17

Descriptive Statistics for Algebra Pretest and Posttest for Experimental and Control Groups

Variable Group	Mean	*N*	SD	SEM
Algebra Pretest Experimental	16.56	54	5.493	.788
Control	13.89	39	5.493	.748
Total	15.44	93	5.396	.560
Algebra Posttest Experimental	20.26	54	6.674	.772
Control	19.67	39	6.674	1.398
Total	20.01	93	7.080	.734

Table 18

Paired t-Test for Algebra Pretest and Posttest for Experimental (n = 54) and Control (n = 39) Groups

							95% Confidence Interval for Difference		
Variables	*n*	Mean	SD	SE	*t*	df	Sig (2-tailed)	Lower	Upper
Pretest Posttest Experimental	54	-3.7	6.061	.825	-4.490	53	.0001	-5.36	-2.05
Pretest Posttest Control	39	-5.769	9.109	1.459	-3.955	38	.001	-8.722	-2.816
Pretest Posttest Both	93	-4.570	7.516	.779	-5.864	92	.0001	-6.118	-3.022

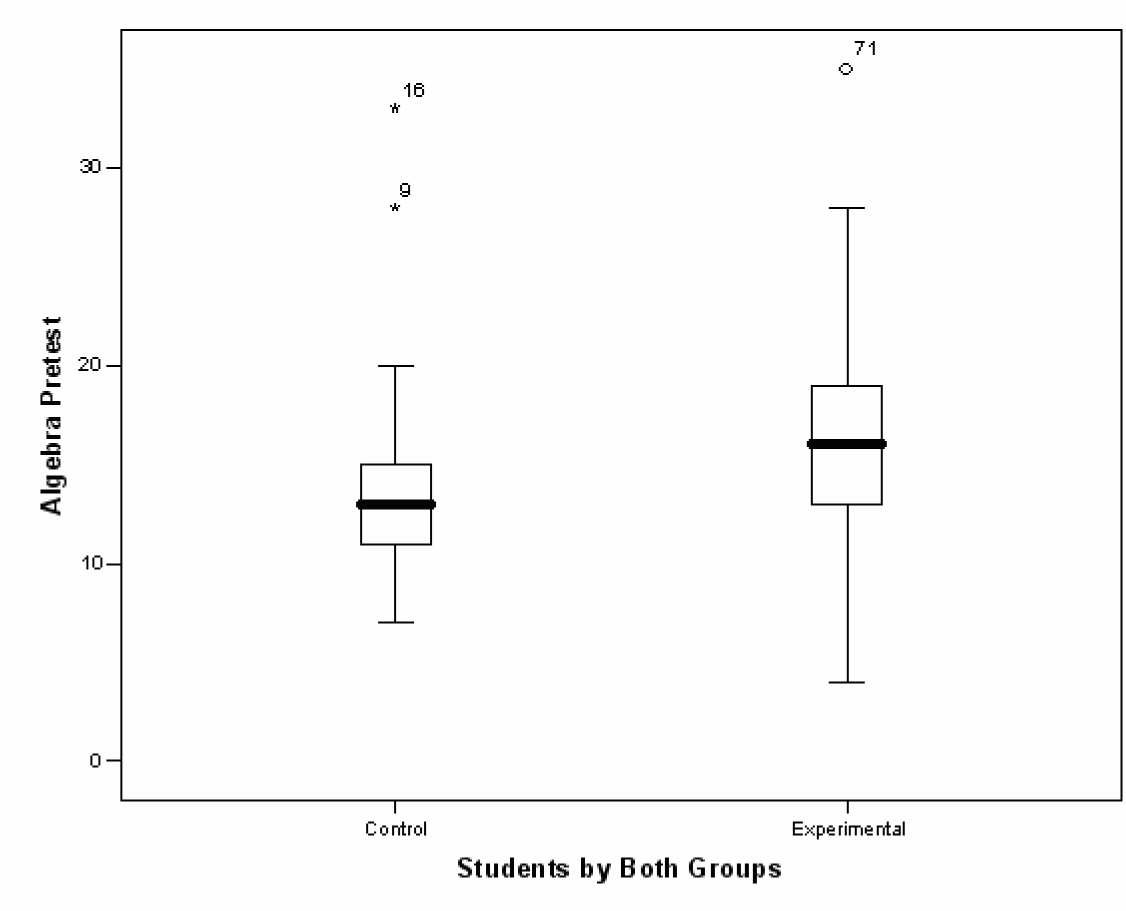

Figure 5. Boxplots of Algebra Pretest for Experimental and Control Groups.

Differences on Mathematics Anxiety Rating Scale

The Mathematics Anxiety Rating Scale test, both the pretest and posttest, were administered to the Experimental group (n = 54) and the Control group (n =39). The Mathematics Anxiety Rating Scale (MARS) consisted of 30 questions on perceived anxiety of mathematics students. The minimum possible points on this test were 30, indicating no anxiety, and maximum possible points of 150, indicating extreme anxiety. The students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest near

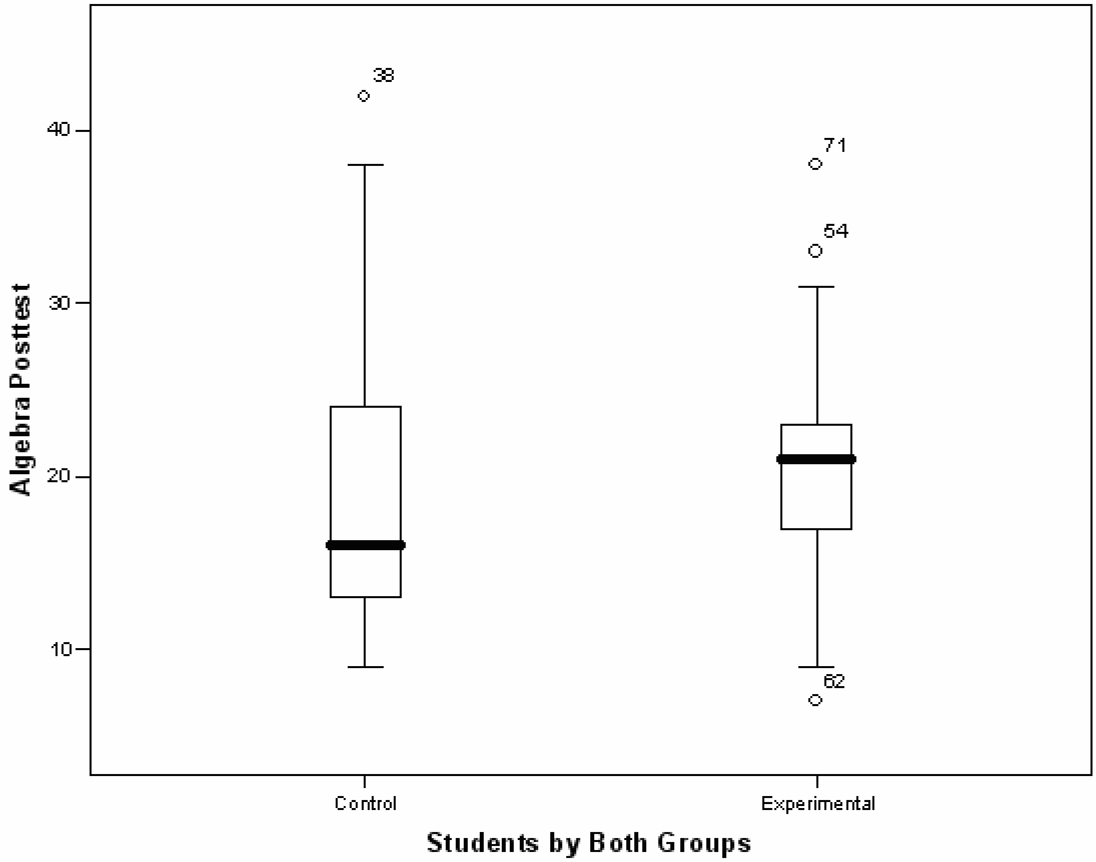

Figure 6. Boxplots of Algebra Posttest for Experimental and Control Groups.

the end of the semester. Lower scores on the posttest MARS indicate less anxiety. A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MARS given to the Experimental group and the Control group. A scatterplot was first examined to view the relationship between the pretest and posttest MARS, as shown in Figures 7 to 9. A positive correlation can be seen in the scatterplots. The relationship between pretest and posttest MARS was investigated using a Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables (r = .550, n =54, p = .0001), with higher scores on the pretest associated with higher scores on the posttest for the Experimental group. There was a medium positive correlation between the two variables (r = .627, n = 39, p = 0001), with higher scores on the pretest associated with higher scores on the posttest for the Control group. There was also a medium positive correlation between both groups (Experimental and Control) between the two variables (r = .585, n = 93, p = 0001), with higher scores on the pretest associated with higher scores on the posttest.

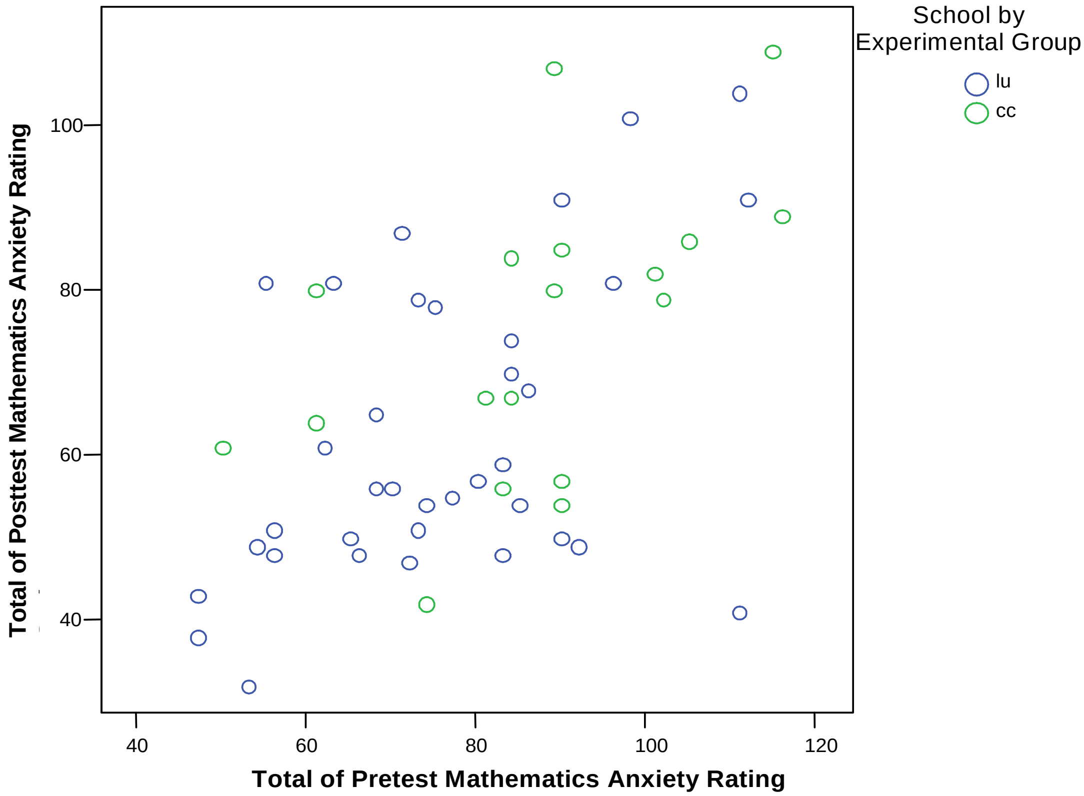

Figure 7. Scatterplot of Pretest Mathematics Anxiety Rating Scale as Independent Variable and Posttest Mathematics Anxiety Rating Scale as Dependent Variable of Experimental Group Only.

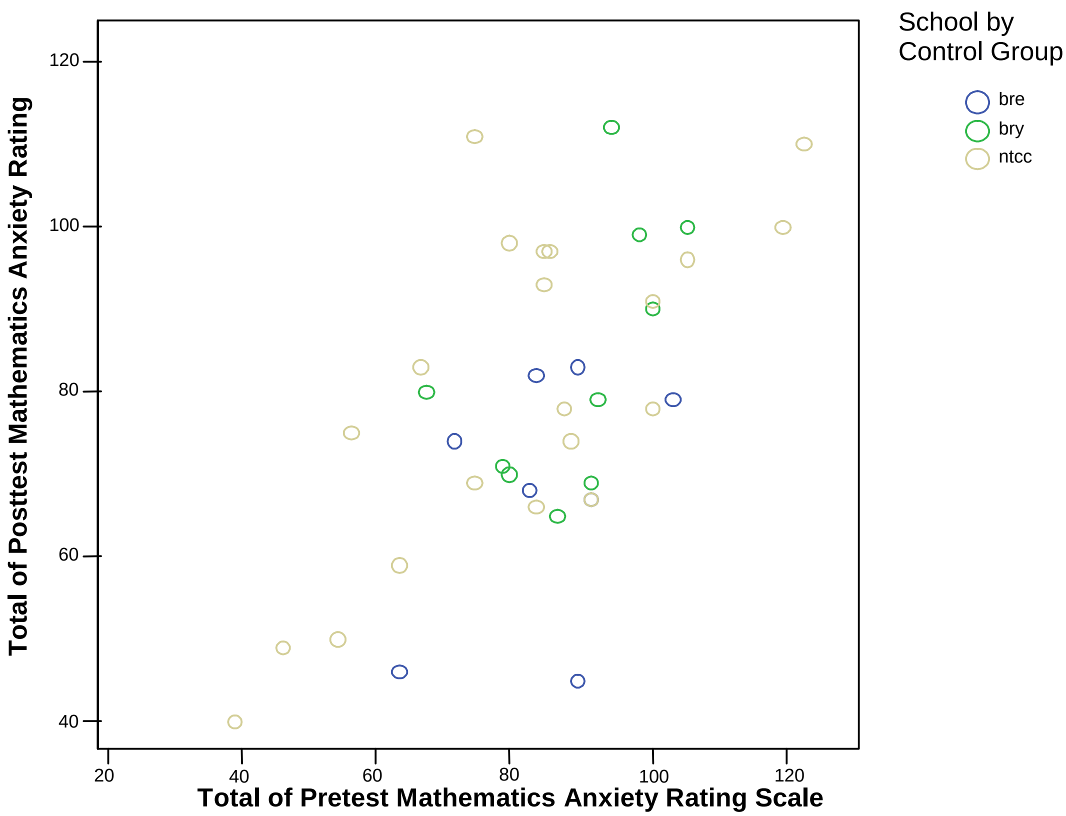

Figure 8. Scatterplot of Pretest Mathematics Anxiety Rating Scale as Independent Variable and Posttest Mathematics Anxiety Rating Scale as Dependent Variable of Control Group Only.

A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the MARS. Descriptive statistics are presented in Table 19. There was a statistically significant difference from pretest (M = 79.54, SD = 18.01) to posttest (M = 66.61, SD = 18.95), as shown in Table 20 for the Experimental group ($t(53)$ = 5.41, $p < .001$). There was not a statistically significant difference from pretest (M = 83.59, SD = 18.04) to posttest (M = 78.46, SD = 18.67), as shown in Table 21 for the Control group ($t(38)$ = 2.02, p =.051). There was a statistically significant difference from pretest (*M* = 81.24, *SD* = 18.070) to posttest (*M* = 71.58, *SD* = 19.632), as shown in Table 22 for both groups ($t(92) = 5.40$, $p < .001$). The Cohen's $d = .736$ (Experimental group), Cohen's $d = .424$ (Control group), and Cohen's $d = .560$ (for both groups) indicated a medium effect size. Boxplots for pretest and posttest for Experimental and Control groups are presented in Figures 10 and 11, respectively.

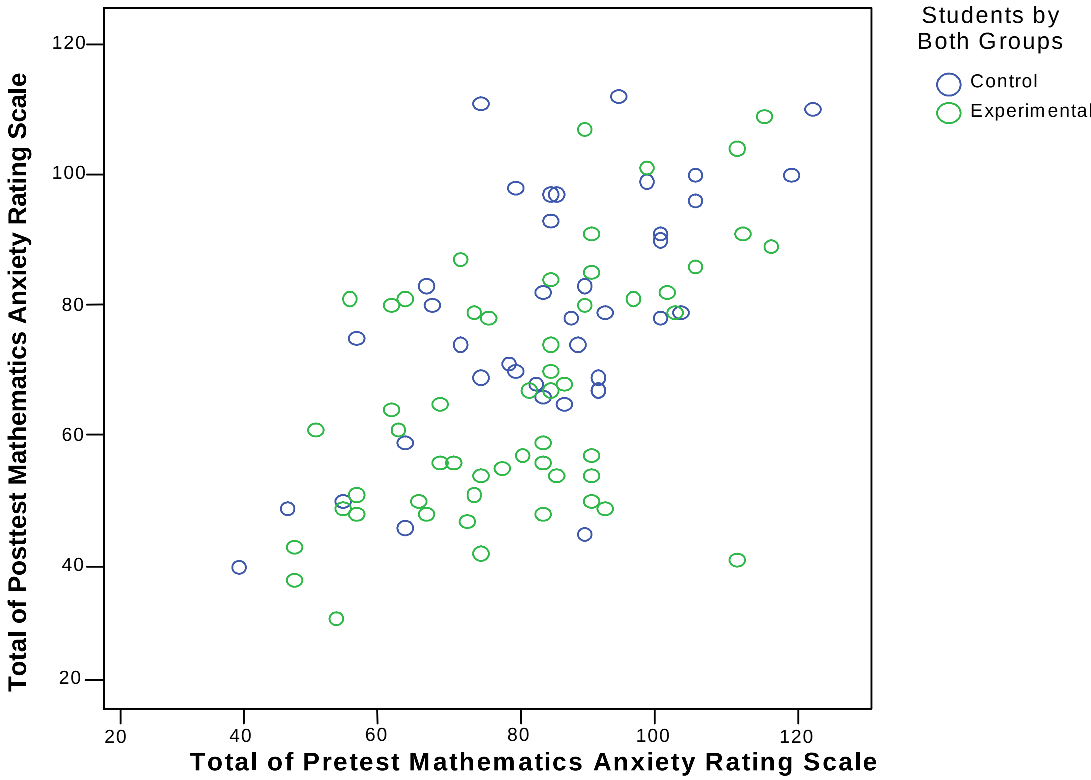

Figure 9. Scatterplot of Pretest Mathematics Anxiety Rating Scale as Independent Variable and Posttest Mathematics Anxiety Rating Scale as Dependent Variable of Both Groups.

Table 19

Descriptive Statistics for Pretest and Posttest Mathematics Anxiety Rating Scale for Experimental (n = 54), Control (n = 39), and Total (n = 93)

Variable	Group	Mean	*N*	SD	SEM
MARS Pretest	Experimental	79.54	54	18.006	2.458
	Control	83.59	39	18.042	2.889
	Total	81.24	93	18.070	1.874
MARS Posttest	Experimental	66.61	54	18.952	2.579
	Control	78.46	39	18.666	2.989
	Total	71.58	93	19.632	2.036

Table 20

Paired t-Test for Pretest and Posttest Mathematics Anxiety Rating Scale for Experimental Group Only

								95% Confidence Interval for Difference	
Variables	*n*	Mean	SD	SE	*t*	df	Sig (2-tailed)	Lower	Upper
Pretest Posttest	54	12.93	17.573	2.391	5.405	53	.0001	8.13	17.72

Table 21

Paired t-Test for Pretest and Posttest Mathematics Anxiety Rating Scale for Control Group Only

								95% Confidence Interval for Difference	
Variables	*n*	Mean	SD	SE	*t*	df	Sig (2-tailed)	Lower	Upper
Pretest Posttest	39	5.13	15.870	2.541	2.018	38	.051	-.02	10.27

Table 22

Paired t-Test for Pretest and Posttest Mathematics Anxiety Rating Scale for Both Groups

							95% Confidence Interval for Difference		
Variables	*n*	Mean	SD	SE	*t*	df	Sig (2-tailed)	Lower	Upper
Pretest Posttest	93	9.66	17.231	1.787	5.404	92	.0001	6.11	13.20

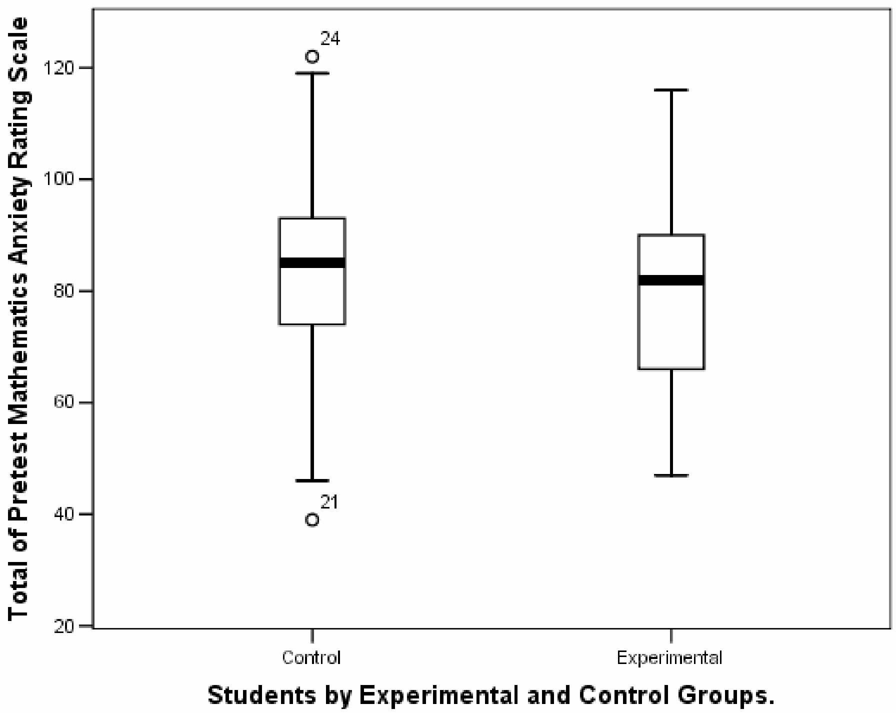

Figure 10. Boxplots of Pretest MARS.

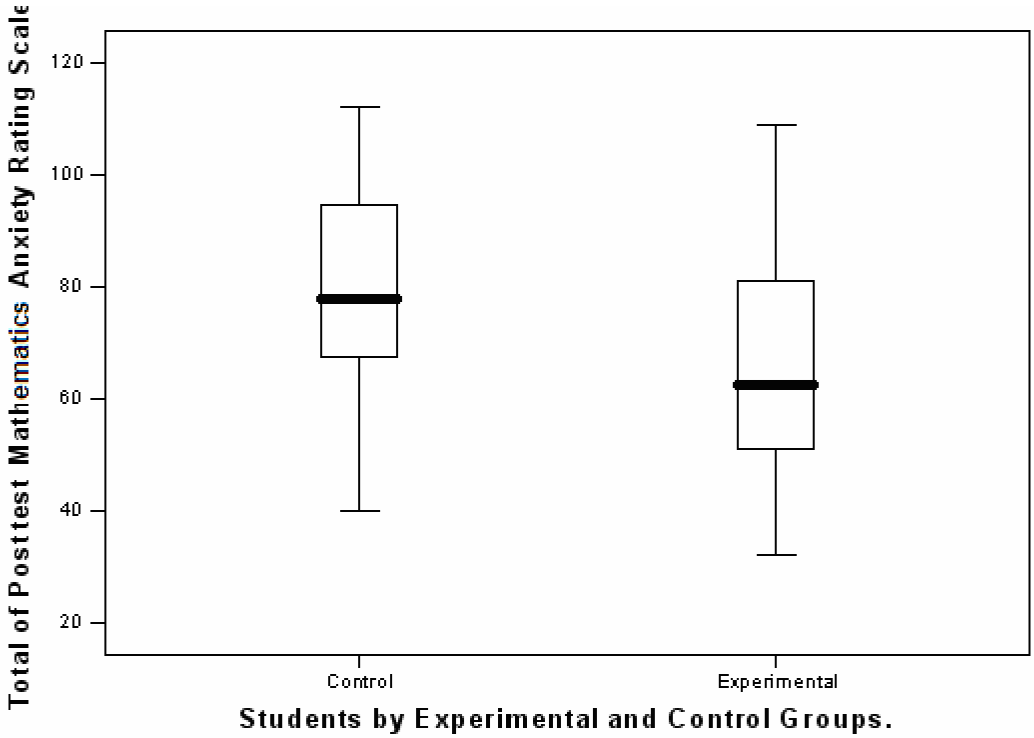

Figure 11. Boxplots of Posttest MARS.

Differences on Mathematics Attitude

A Fennama-Sherman Mathematics Attitude (MA) test was given to the Experimental group (n = 54) and the Control group (n =39). The Mathematics Attitude (MA) test consists of 47 questions, divided into four categories: (a) confidence toward mathematics (MAC), (b) usefulness of mathematics (MAU), (c) teacher influence (MAT), and (d) male dominance (MAM). The four categories test for positive and negative attitudes. The students were given the pretest in September and the posttest in December. The intervention began as soon as the pretest and posttest were completed. A Pearson r correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MA given to the Experimental group and Control group. Scatterplots of the relationship between the pretest and posttest MA are presented in Figures 12 to 14. Scatterplots of the entire sample, including Experimental only and Control group only, as well as a scatterplot of both groups, are reported. There was a positive correlation, as can be seen in the scatterplots. An analysis was conducted on the four components for further investigation reported in question V.

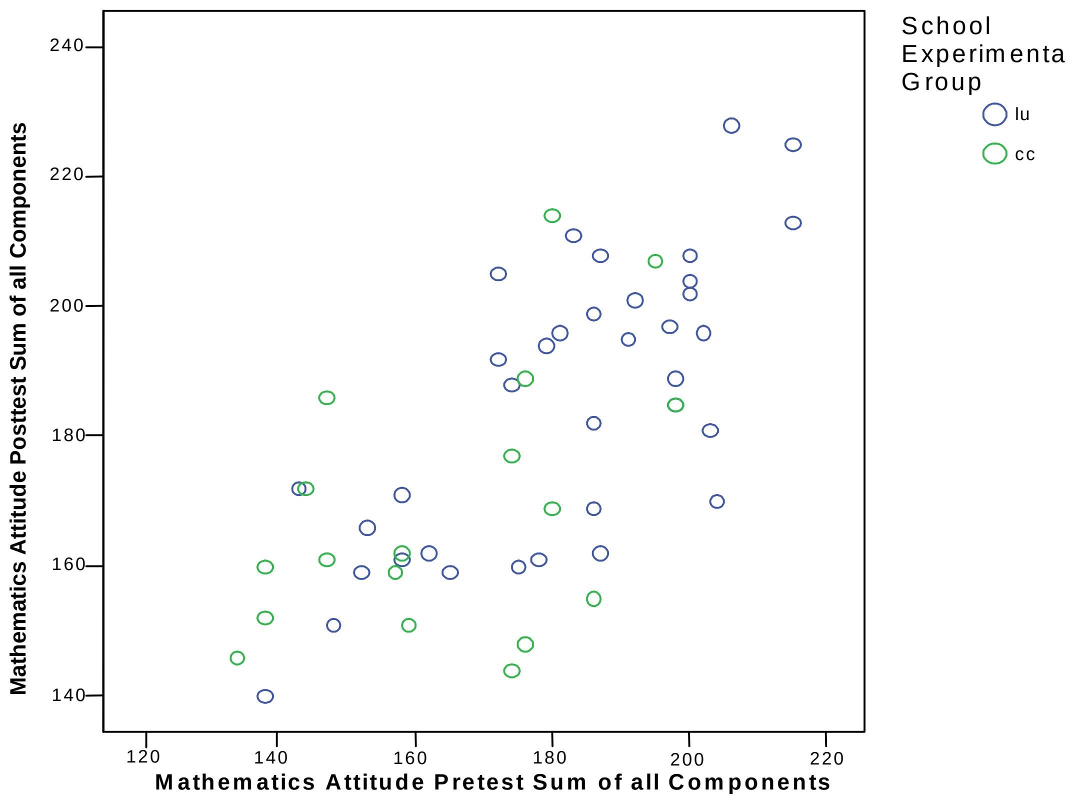

Figure 12. Scatterplot of Pretest Mathematics Attitude as Independent Variable and Posttest Mathematics Attitude as Dependent Variable of Experimental Group Only.

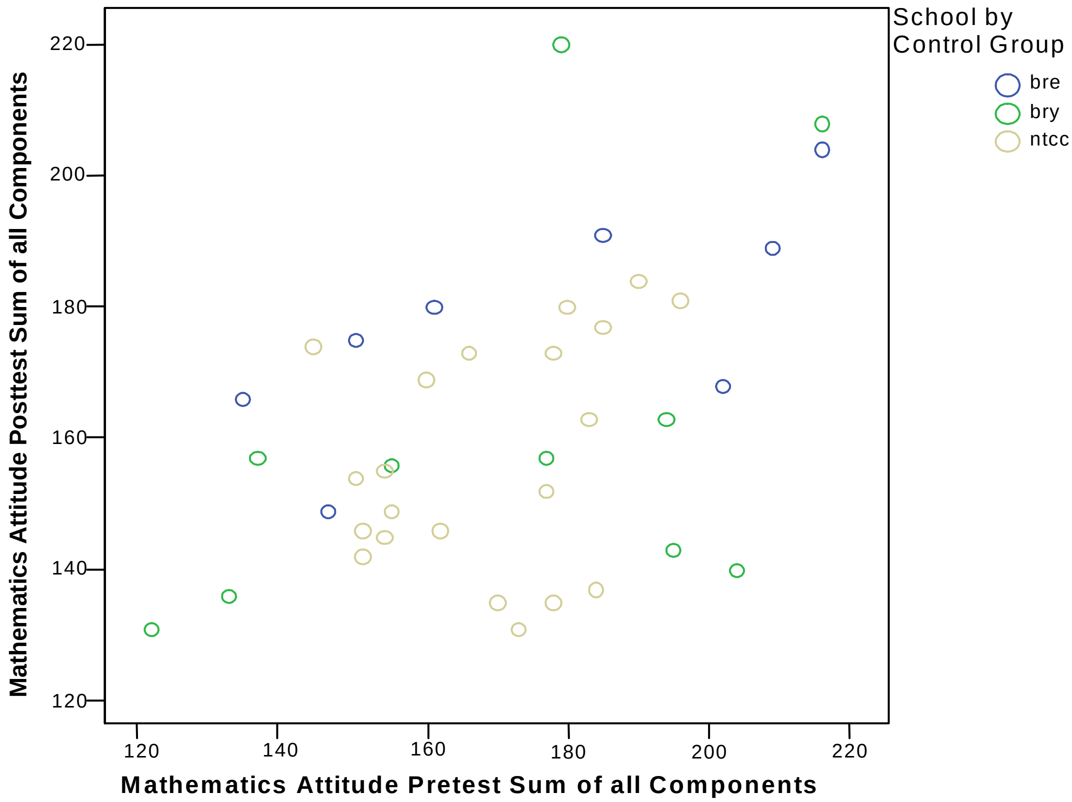

Figure 13. Scatterplot of Pretest Mathematics Attitude as Independent Variable and Posttest Mathematics Attitude as Dependent Variable of Control Group Only.

The relationship between pretest and posttest MA was investigated using a Pearson *r* correlation coefficient analyses. There was a medium positive correlation between the two variables comparing Experimental only (r = .693, n =54, p = .001), with higher scores on the pretest associated with higher scores on the posttest for the Experimental group. There was a medium positive correlation between the two variables comparing Control group only (r = .466, n = 39, p = 003) with higher scores on the pretest associated with higher scores on the posttest for the Control group. There was a

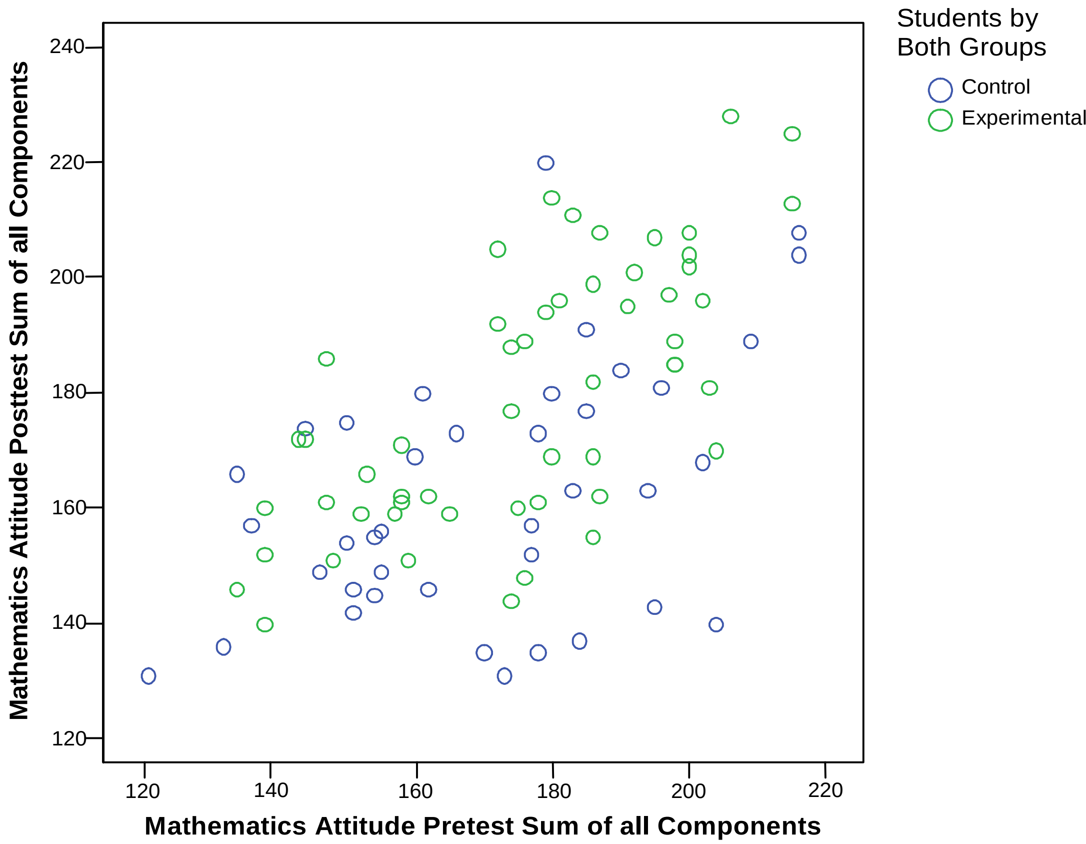

Figure 14. Scatterplot of Pretest Mathematics Attitude (47 Questions) as Independent Variable and Posttest Mathematics Attitude (47 Questions) as Dependent Variable of Both Groups.

medium positive correlation between both groups (Experimental and Control) between the two variables (r = .592, n = 93, p = 0001), with higher scores on the pretest associated with higher scores on the posttest.

A paired-samples t-test was conducted to evaluate the impact of the intervention on students' scores on the MA. There was not a statistically significant difference for the Experimental group from the pretest (M = 176.02, SD = 21.77) to the posttest (M =

178.61, S*D* = 22.61), as shown in Table 23 ($t(53) = -1.52$, $p = .136$). There was a statistically significant difference for the Control group from the pretest (*M* = 170.59, S*D* = 23.10) to posttest (*M* = 162.41, S*D* = 22.09) as shown in Table 23 ($t(38) = 2.15$, $p = .038$). There was not a statistically significant difference between the Experimental and Control groups from the pretest (*M* = 173.74, S*D* = 22.724) to the posttest (*M* = 172.40, S*D* = 23.852), as shown in Table 23, ($t(93) = .592$, $p = .540$). Boxplots for pretest and posttest for Experimental and Control groups are presented in Figures 15 and 16.

Table 23

Descriptive Statistics for Pretest and Posttest Mathematics Attitude for Experimental, Control, and Both Groups

Measure	Mean	*n*	SD	SEM
MA Pretest Experimental	176.02	54	21.770	2.963
MA Posttest Experimental	179.61	54	22.610	3.077
MA Pretest Control	170.59	39	23.909	3.828
MA Posttest Control	162.41	39	22.093	3.538
MA Pretest Both	173.74	93	22.724	2.356
MA Posttest Both	172.40	93	23.852	2.473

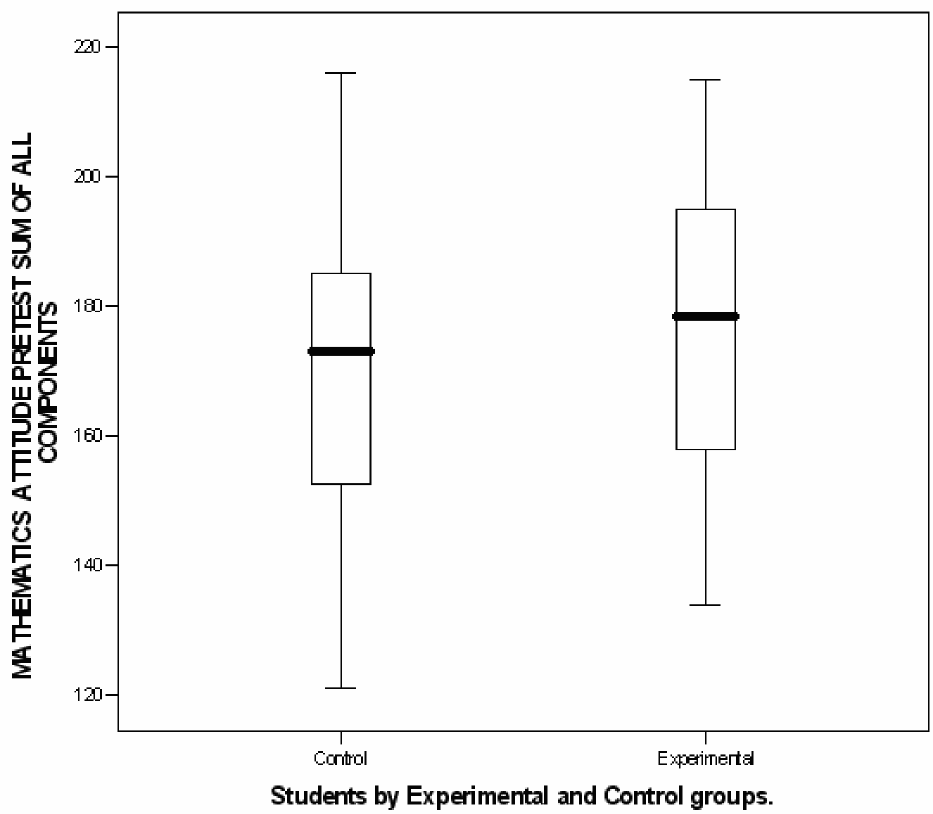

Figure 15. Boxplots of Mathematics Attitude Pretest for Both Groups.

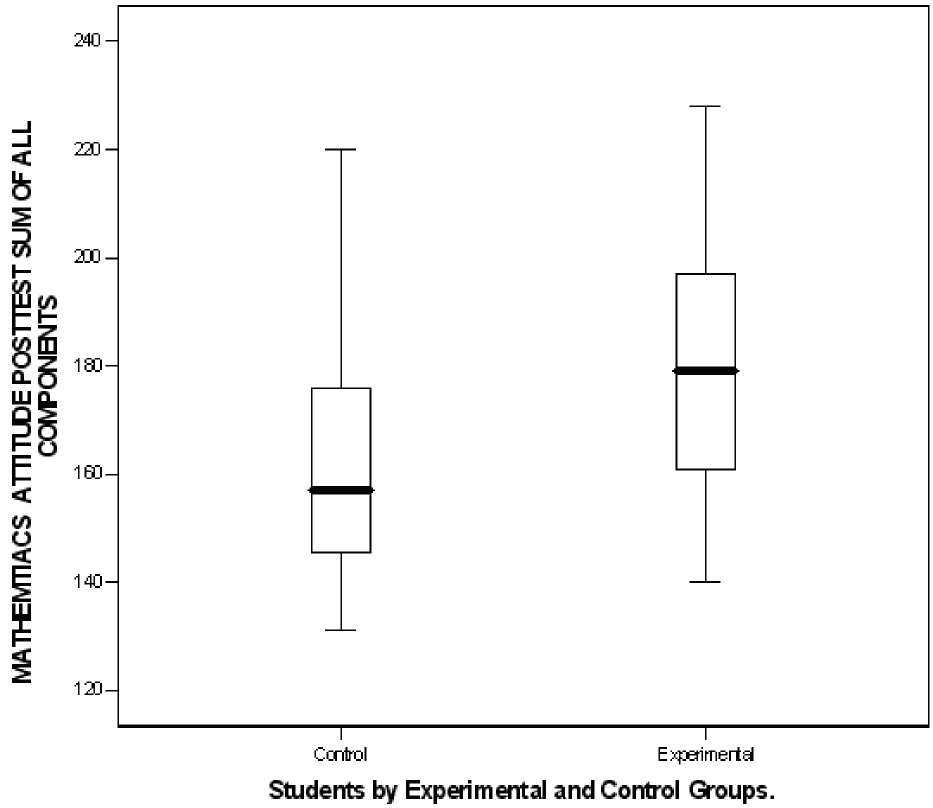

Figure 16. Boxplots of Mathematics Attitude Posttest for Both Groups.

Research Question III

Are there differential mathematics effects for either group based on demographic factors such as gender, age, ethnicity, number of mathematics courses taken in the past, and degree plans?

Gender

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the algebra pretest and posttest by gender with higher scores on the pretest associated with higher scores on the posttest. A scatterplot was first examined to view the relationship between the algebra pretest and posttest seen in Figure 17. A positive correlation can be seen in the scatterplot. Tables 24 to 26 presents the descriptive statistics for the algebra pretest and posttest for the groups of students by gender, with higher scores on the pretest associated with higher scores on the posttest. The relationship between the algebra pretest and posttest was investigated using a Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables: females (r = .626, n =56, p < .001), males (r = .510, n =37, p = .001), and total (r = .585, n =93, p < .001). Boxplots for the algebra pretest and posttest by gender are presented in Figures 18 and 19, respectively. An ANOVA on gain scores was conducted by gender. There was not a statistically significant difference ($F(1, 91) = .345$, p = .558, $\eta^2 < .01$).

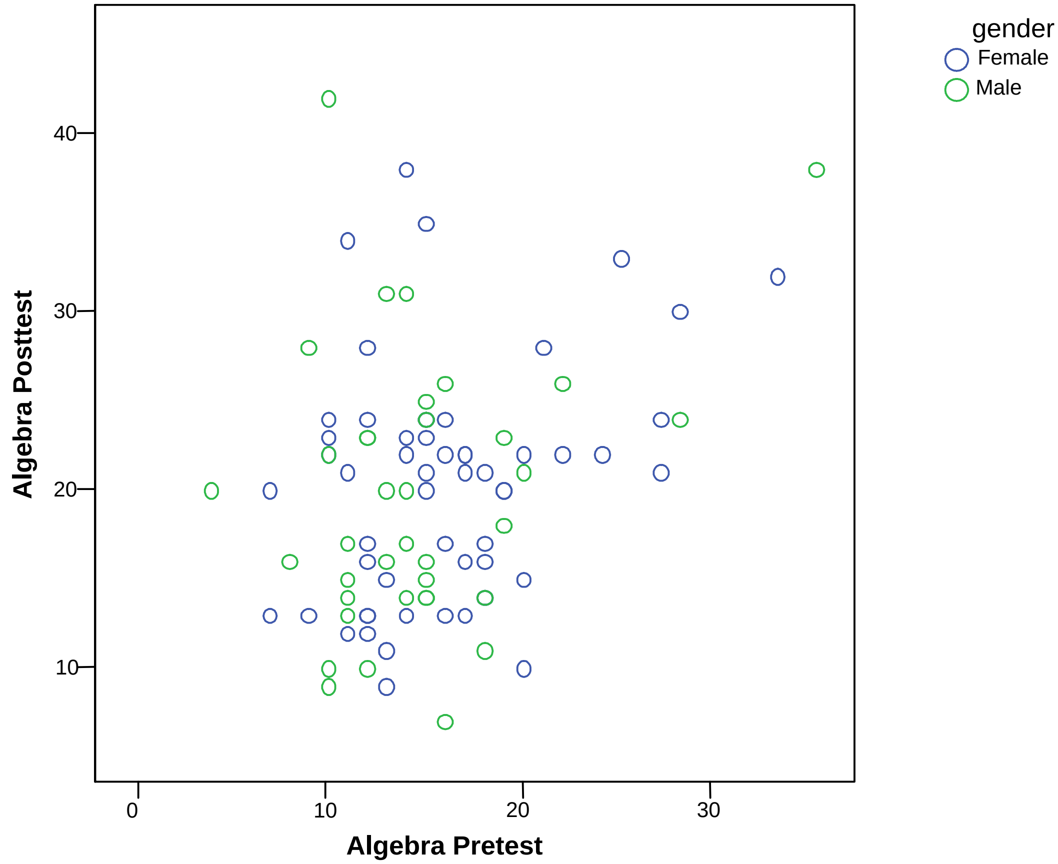

Figure 17. Scatterplot of Algebra Pretest and Algebra Posttest of Experimental and Control group by Gender.

Table 24

Descriptive Statistics for Algebra Pretest and Posttest for Females and Males

Variable	Group	Mean	*n*	SD	SEM
Algebra Pretest	Female	16.05	56	5.269	.725
	Male	14.51	37	5.526	.872
	Total	15.44	93	5.396	.560
Algebra Posttest	Female	20.25	56	6.623	.959
	Male	19.64	37	7.800	1.153
	Total	20.01	93	7.080	.734

Table 25

Descriptive Statistics for Pretest and Posttest Algebra Test by Gender

				95% Confidence Interval	
Dependent Variable	GEN	Mean	SE	Lower Bound	Upper Bound
Algebra Pretest	Female	16.055	.725	14.615	17.494
	Male	14.553	.872	12.821	16.284
Algebra Posttest	Female	20.309	.959	18.405	22.213
	Male	19.579	1.153	17.288	21.870

Table 26

Descriptive Statistics for Pretest and Posttest Algebra Test for Experimental and Control Groups of Students by Gender Calculated Separately

Variable	Gender	Group	Mean	SD	*N*
Algebra Pretest	Female	Control	15.00	5.920	22
		Experimental	16.76	4.841	33
		Total	16.05	5.317	55
	Male	Control	12.47	2.764	17
		Experimental	16.24	6.503	21
		Total	14.55	5.456	38
	Total	Control	13.90	4.919	39
		Experimental	16.56	5.493	54
		Total	15.44	5.396	93
Algebra Posttest	Female	Control	20.59	8.964	22
		Experimental	20.12	4.715	33
		Total	20.31	6.669	55
	Male	Control	18.47	8.538	17
		Experimental	20.48	7.047	21
		Total	19.58	7.706	38
	Total	Control	19.67	8.731	39
		Experimental	20.26	5.674	54
		Total	20.01	7.080	93

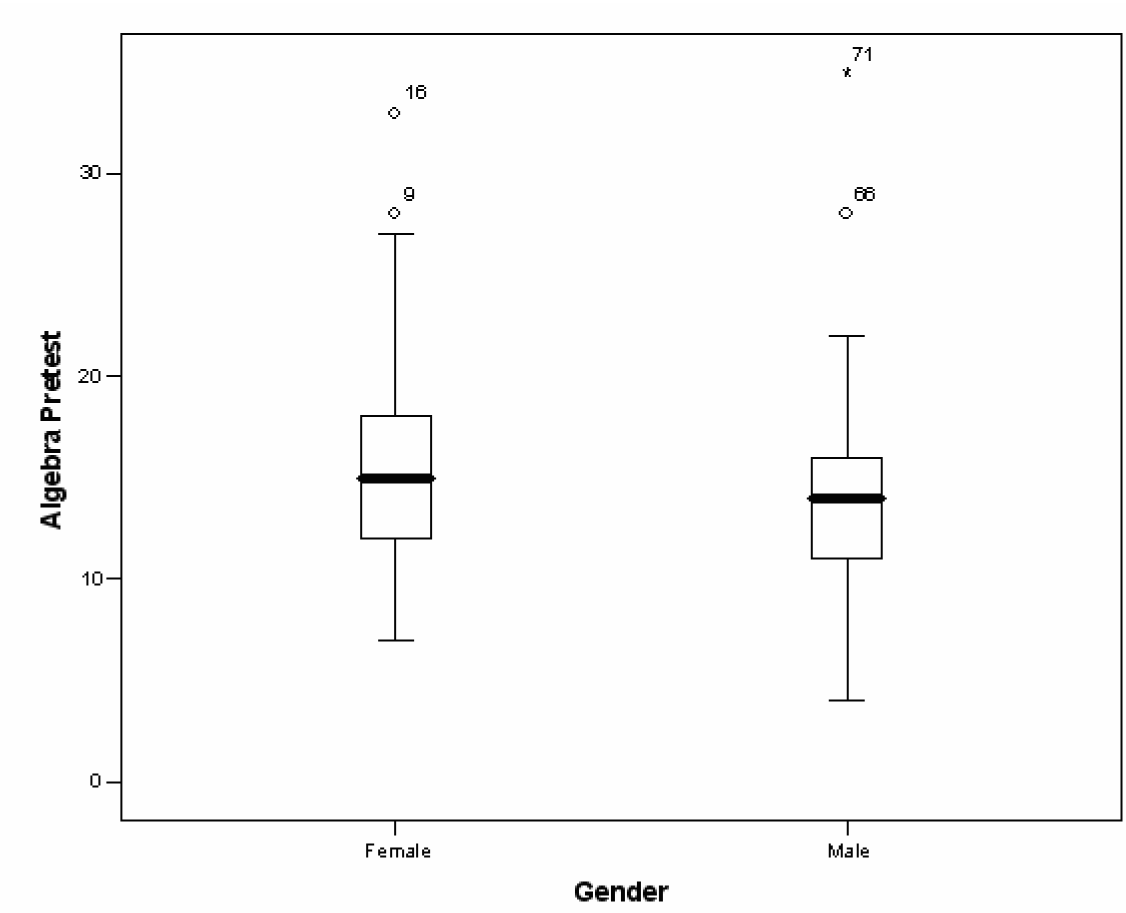

Figure 18. Boxplots of Algebra Pretest for Females and Males.

Age

A Pearson *r* correlation was conducted to test differences between age groups including: age eighteen (*n*= 52, *r*=.379, *p*=.005), age nineteen (*n*= 11, *r*=-.204, *p*=.548), age twenty (*n*= 8, *r*=.867, *p*=.005), age twenty-one (*n*= 5, *r*=.354, *p*=.559), age twenty-two (*n*= 1), age twenty-three (*n*= 3, *r*=-.568, *p*=.615), age twenty-five (*n*= 2), and (*n*= 1) for age groups twenty-six, thirty-three, thirty-seven, thirty-eight, forty, fifty, and fifty-two, with an addition of (*n*= 2) for age group thirty-nine on algebra pretests and posttests. Descriptive statistics are shown in Table 27.

Ethnicity

Descriptive statistics for ethnicity are shown in Table 28. An ANOVA on gain scores was conducted by ethnicity. There was not a statistically significant difference ($F(3, 89) = .058$, $p = .982$, $\eta^2 < .01$).

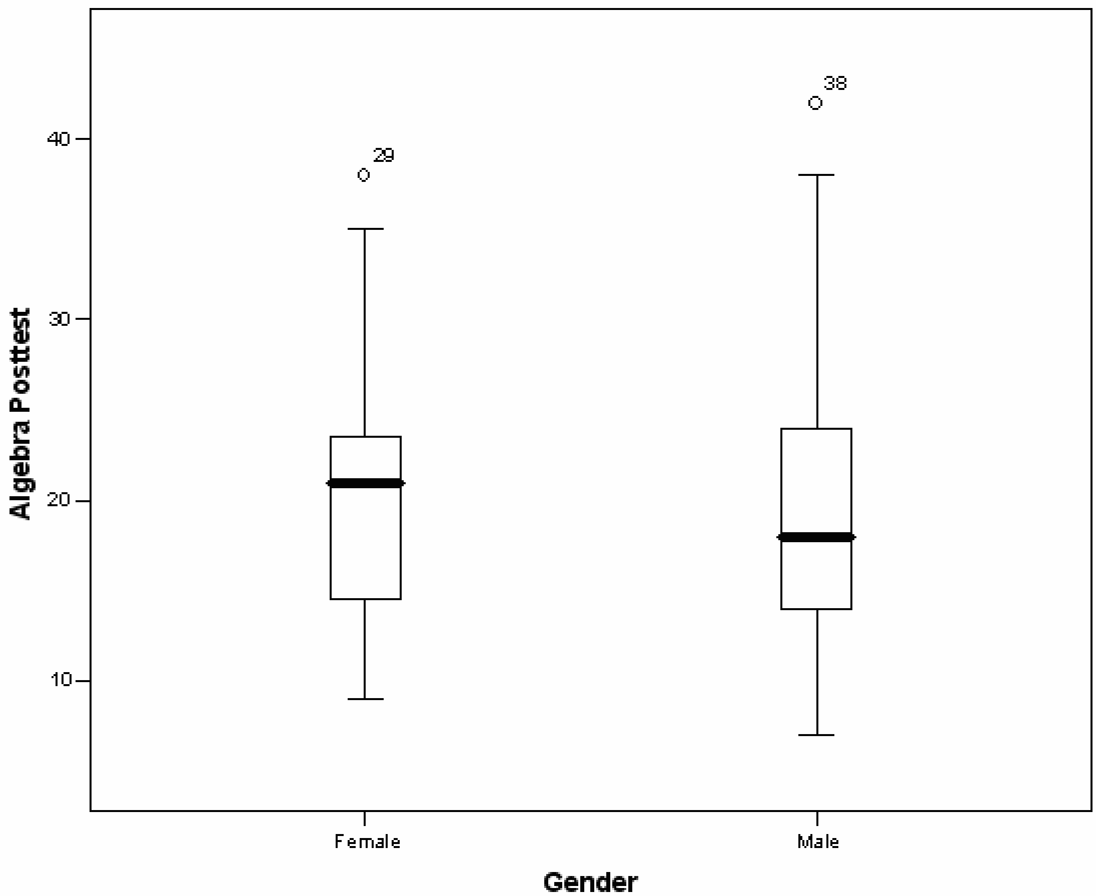

Figure 19. Boxplots of Algebra Posttest for Females and Males.

Table 27

Descriptive Statistics for Algebra Pretest and Posttest for Experimental and Control Groups of Students by Age Calculated Separately

Variable	Age Group	Mean	SD	*N*
Algebra Pretest	18	15.88	4.83	51
	19	14.33	3.49	12
	20	16.63	7.63	8
	21	4.20	7.76	5
	22	15.00	.00	1
	23	14.33	6.66	3
	25	15.50	2.12	2
	26	11.00	.00	1
	29	12.00	.00	1
	33	12.00	.00	1
	37	12.00	.00	1
	38	33.00	.00	1
	39	8.50	2.12	2
	40	14.00	.00	1
	50	15.00	.00	1
	52	10.00	.00	1
	Total	15.34	5.33	92
Algebra Posttest	18	19.04	5.87	51
	19	19.17	7.69	12
	20	21.00	8.25	8
	21	17.80	5.12	5
	22	14.00	.00	1
	23	26.67	6.43	3
	25	15.00	1.41	2
	26	21.00	.00	1
	29	24.00	.00	1
	33	17.00	.00	1
	37	13.00	.00	1
	38	32.00	.00	1
	39	27.50	20.51	2
	40	38.00	.00	1
	50	24.00	.00	1
	52	22.00	.00	1
	Total	19.87	6.99	92

Table 28

Descriptive Statistics for Algebra Pretest and Posttest for Experimental and Control Groups of Students by Ethnicity Calculated Separately

Variable	Ethnicity	Mean	SD	*N*
Algebra Pretest	Caucasian	15.891	5.735	64
	African	13.778	4.919	9
	Hispanic	14.333	4.515	15
	Other	16.000	4.183	5
	Total	15.441	5.396	93
Algebra Posttest	Caucasian	20.375	7.414	64
	African	19.333	5.657	9
	Hispanic	18.800	5.772	15
	Other	20.200	9.884	5
	Total	20.011	7.080	93

Research Question IV

Do differences emerge between the two groups of students in their perceived level of mathematics anxiety?

The Mathematics Anxiety Rating Scale (MARS) test was given to the Experimental group (n = 54) and the Control group (n =39). The MARS consists of 30 questions relating the perceived anxiety of mathematics students when considering taking a mathematics test and calculating mathematical problems. The students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest near the end of the semester.

A Pearson r correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MARS given to the

Experimental

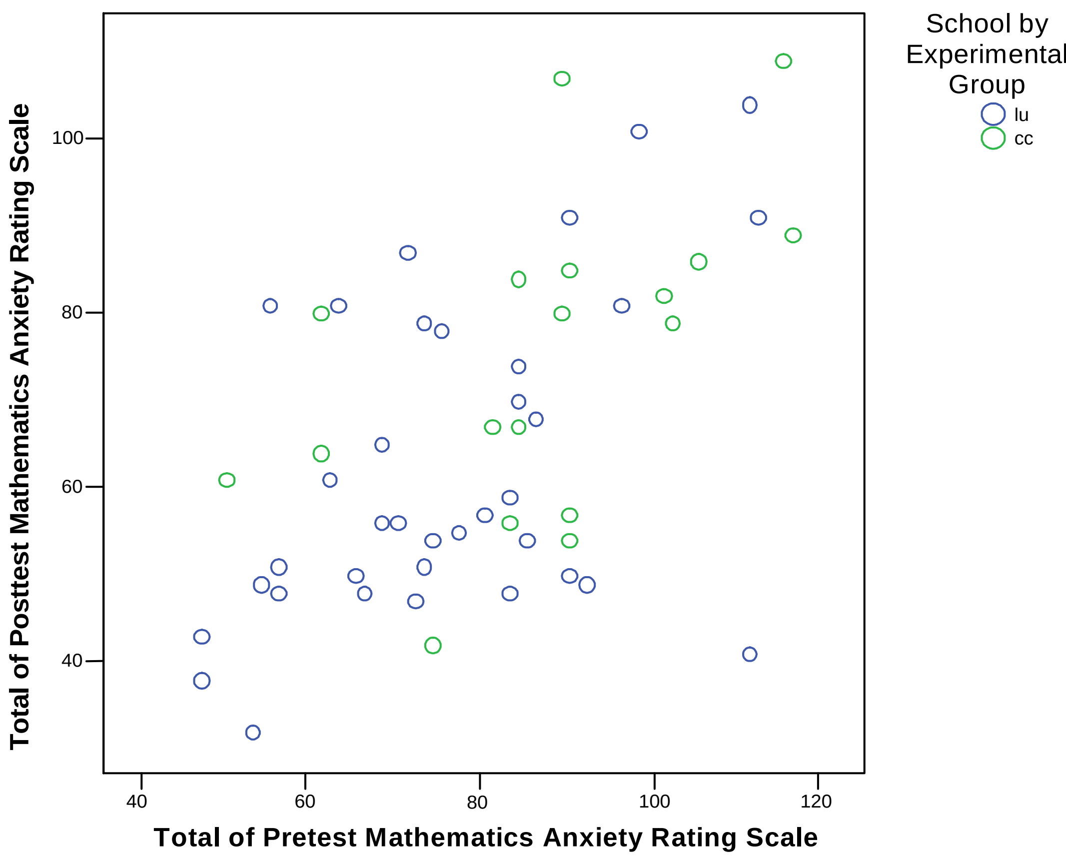

Figure 20. Scatterplot of Pretest Mathematic Anxiety Rating Scale as Independent Variable and Posttest Mathematics Anxiety Rating Scale as Dependent Variable of Experimental Group Only.

group and Control group. A scatterplot was first examined to view the relationship between the pretest and posttest MARS, as seen in Figures 20 to 22. A positive correlation can be seen in the scatterplot.

Descriptive statistics are shown in Table 29, with higher scores on the pretest associated with higher scores on the posttest for the Experimental, Control, and both groups. The relationship between pretest and posttest MARS was investigated using a Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables ($r = .550$, $n = 54$, $p < .001$). There was a medium positive correlation between the two variables ($r = .627$, $n = 39$, $p < .001$). There was also a medium positive correlation between the two groups (Experimental and Control) between the two variables ($r = .585$, $n = 93$, $p < .001$) shown in Figures 21 and 22.

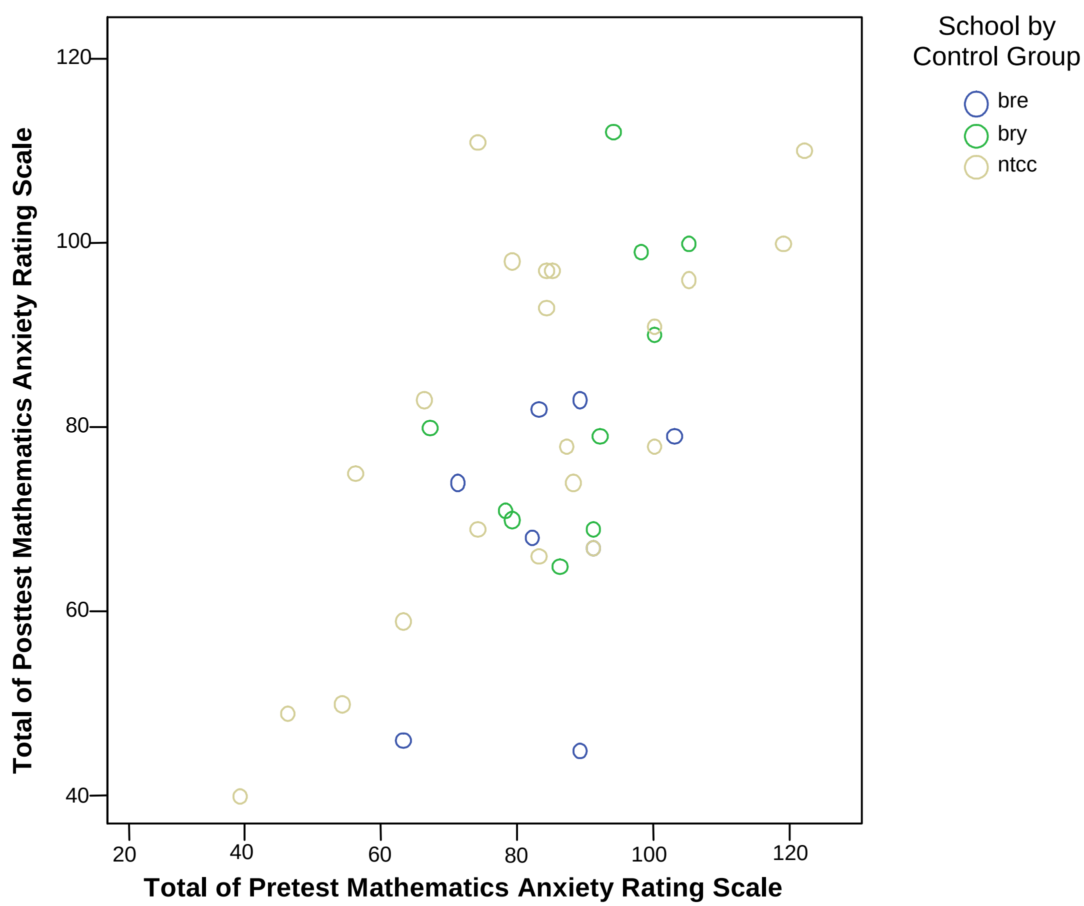

Figure 21. Scatterplot of Pretest Mathematics Anxiety Rating Scale as Independent Variable and Posttest Mathematics Anxiety Rating Scale as Dependent Variable of Control Group Only.

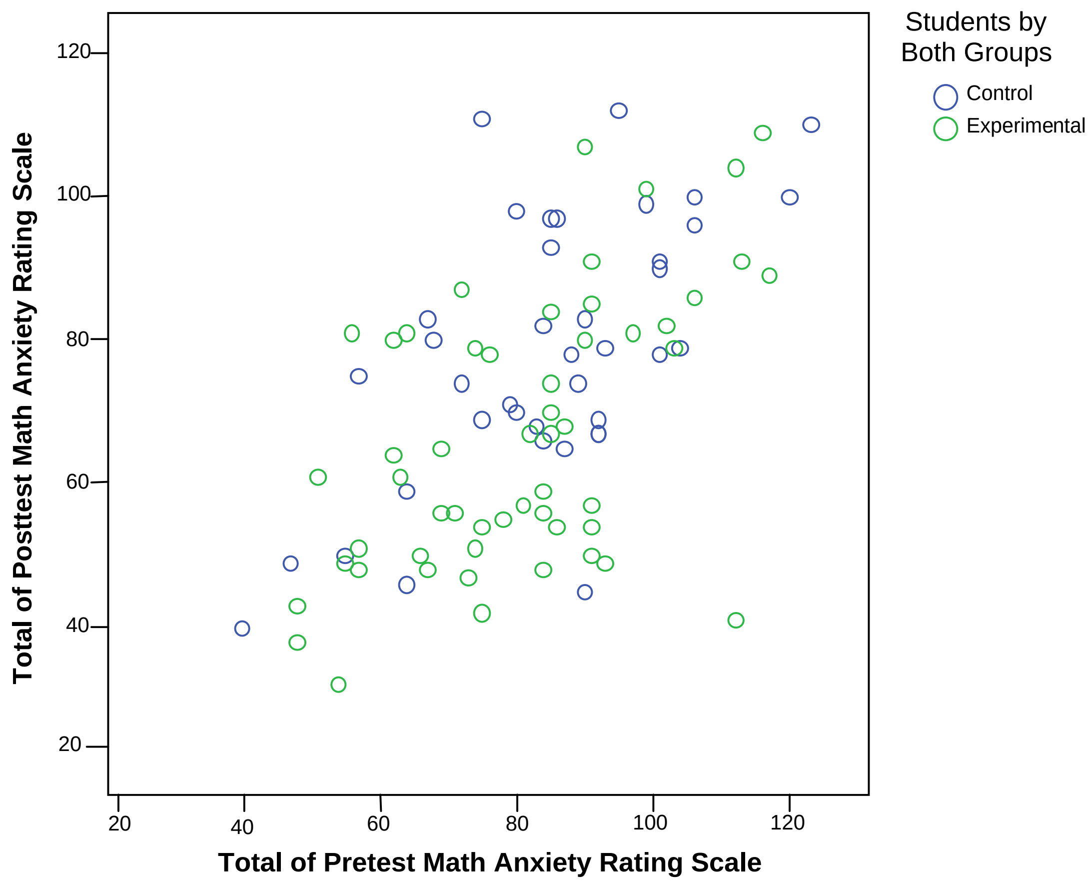

Figure 22. Scatterplot of Pretest Mathematics Anxiety Rating Scale as Independent Variable and Posttest Mathematics Anxiety Rating Scale as Dependent Variable of Both Groups.

Table 29

Descriptive Statistics for Pretest and Posttest Mathematics Anxiety Rating Scale for Experimental, Control, and Both Groups

Variable	Mean	*n*	SD	SEM
MARS Pretest Experimental	79.54	54	18.006	2.458
MARS Posttest Experimental	66.61	54	18.952	2.579
MARS Pretest Control	83.59	39	18.04	2.889
MARS Posttest Control	78.46	39	18.666	2.989
MARS Pretest Both	81.24	93	18.070	1.874
MARS Posttest Both	71.58	93	19.632	2.036

A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the MARS. There was a statistically significant difference for the Experimental group from pretest (M = 79.54, SD = 18.01) to posttest (M = 66.61, SD = 18.59), (t(53) = 5.405, p < .001). There was no statistically significant difference for the Control group from pretest (M = 83.59, SD = 18.042) to posttest (M = 78.46, p = 18.67), (t(38) = 2.018, p = .051). There was a statistically significant difference for both (Experimental and Control) groups from pretest (M = 81.24, SD = 18.07) to posttest (M = 71.58, SD = 19.63), (t(93) = 5.404, p < .001). Cohen's d = .736 (Experimental group), Cohen's d = .424 (Control group), and Cohen's d = .560 (for both groups).

A MANOVA was conducted to test differences between Experimental (n = 54) and Control (n = 39) groups on MARS pretest and posttest. A MANOVA is used for analyses when there are two or more dependent variables. In this case, the two dependent variables are MARS pretest and posttest. This test was designed to measure perceived anxiety associated with mathematics. Box's *M* test indicated the assumption of homogeneity of covariance matrices was met (p = .928). Statistically significant differences did exist between the Experimental and Control groups of students on MARS pretest and posttest ($F(2, 90) = 4.773$, p = .011), with moderate effect size of (η^2 = .10).

Research Question V

Is the student's attitude toward mathematics a factor in student's inability to be successful in Intermediate Algebra?

The Fennama-Sherman Mathematics Attitude (MA) test was administered to the Experimental (n = 54) and the Control (n =39) groups. The MA consists of 47 questions, divided into four categories: (a) Confidence toward mathematics (MAC), (b) Usefulness of mathematics (MAU), (c) Teacher influence (MAT), and (d) Male dominance (MAM). The four categories test for positive and negative attitudes. The test was given in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest near the end of the semester.

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MA given to the Experimental group and Control group. A scatterplot was first examined to view the relationship between the pretest and posttest MA, as seen in Figures 23 through 25. Scatterplots of Experimental only and Control group, as well as both (Experimental and

Control) groups, are reported. A positive correlation between pretest and posttest scores is shown in the scatterplots.

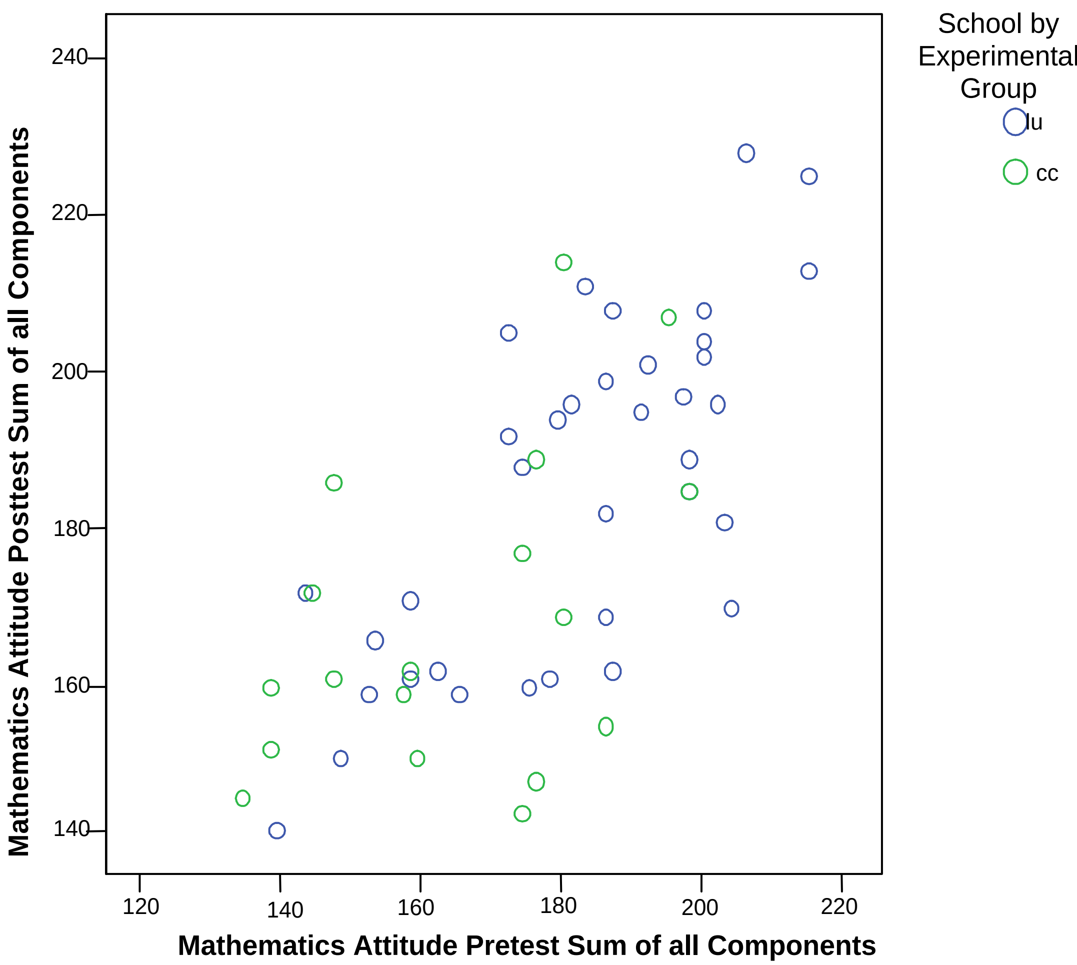

Figure 23. Scatterplot of Pretest Mathematics Attitude (47 Questions) as Independent Variable and Posttest Mathematics Attitude (47 Questions) as Dependent Variable of Experimental Group Only.

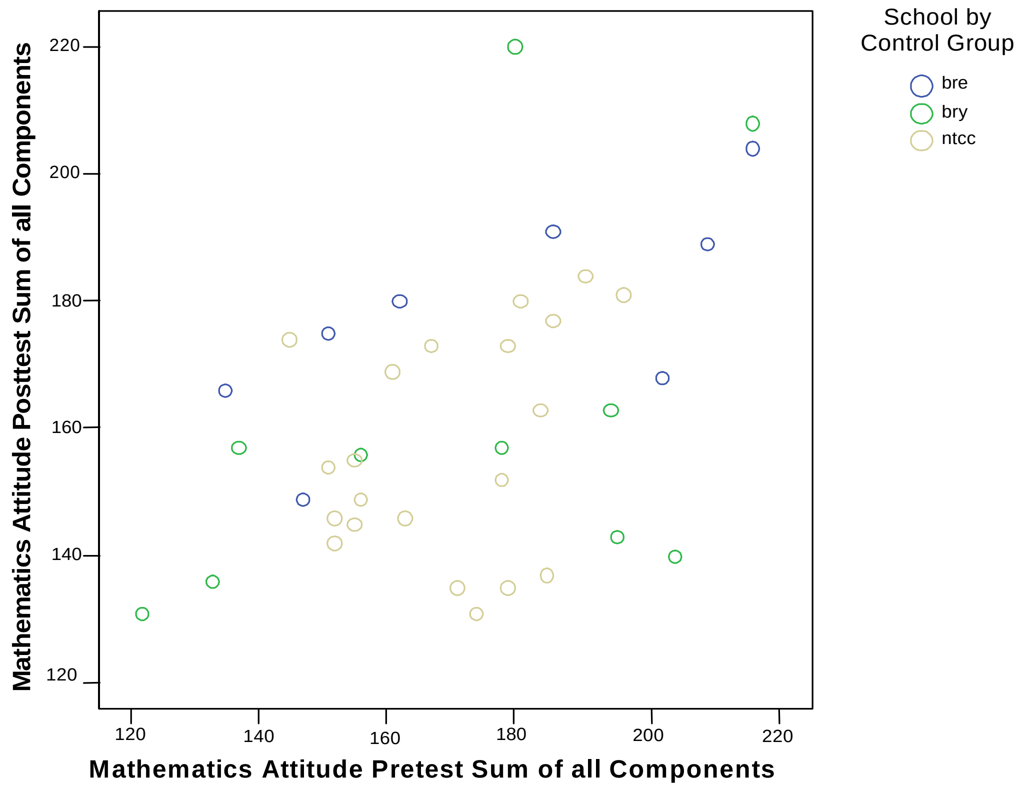

Figure 24. Scatterplot of Pretest Mathematics Attitude (47 Questions) as Independent Variable and Posttest Mathematics Attitude (47 Questions) as Dependent Variable of Control Group Only.

Descriptive statistics are reported in Tables 34 through 36. The relationship between MA pretest and posttest was investigated using a Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables comparing Experimental only (r = .693, n =54, p < .001), with higher scores on the pretest associated with higher scores on the posttest for the Experimental group. There was a medium positive correlation between the two variables comparing the Control group only (r = .466, n = 39, p = .003), with higher scores on the pretest associated with higher scores on the posttest for the Control group. There was a medium positive correlation between the both (Experimental and Control) groups between the two variables (r = .592, n = 93, p < .001), with higher scores on the pretest associated with higher scores on the posttest.

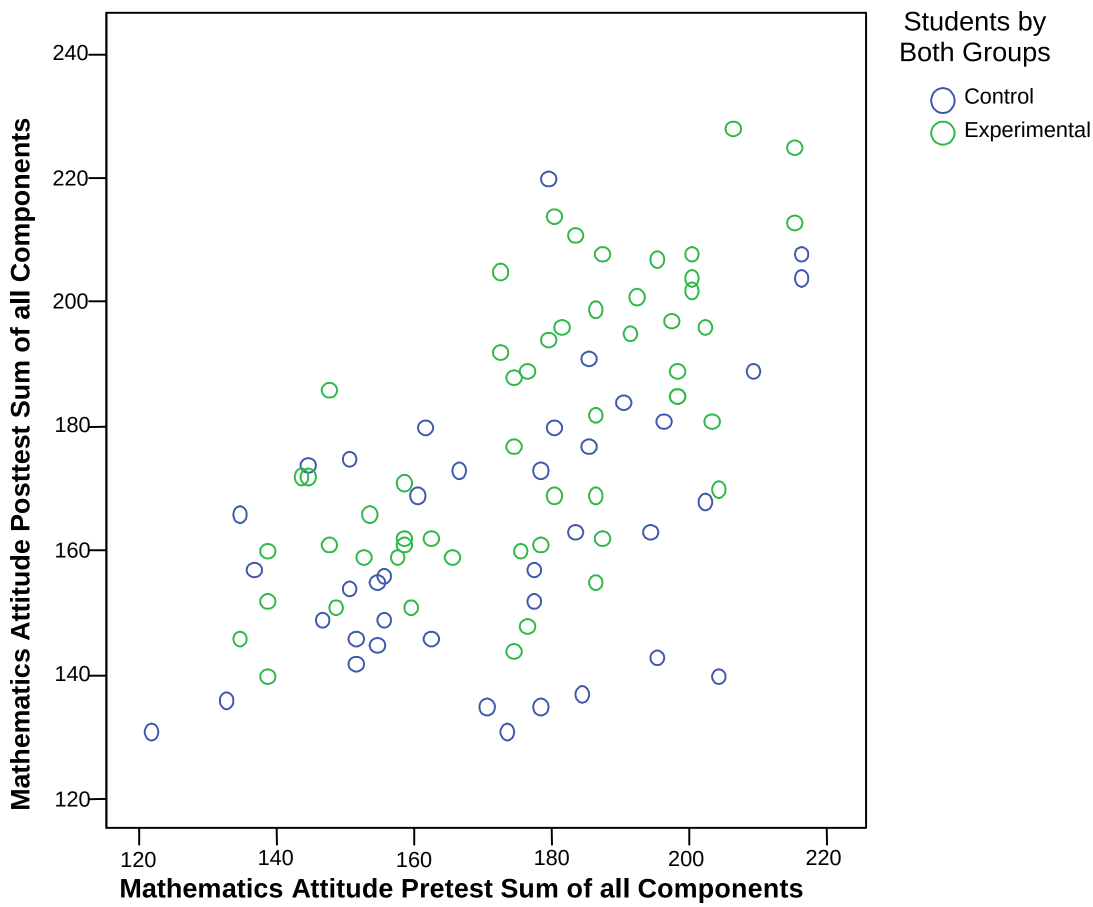

Figure 25. Scatterplot of Pretest Mathematics Attitude (47 Questions) as Independent Variable and Posttest Mathematics Attitude (47 Questions) as Dependent Variable of Both Groups.

Table 30

Descriptive Statistics for Pretest and Posttest Mathematics Attitude for Experimental, Control, and Both Groups

Measure	Mean	*n*	SD	SEM
MA Pretest Experimental	176.02	54	21.770	2.963
MA Posttest Experimental	179.61	54	22.610	3.077
MA Pretest Control	170.59	39	23.909	3.828
MA Posttest Control	162.41	39	22.093	3.538
MA Pretest Both	173.74	93	22.724	2.356
MA Posttest Both	172.40	93	23.852	2.473

A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the MA. There was not a statistically significant difference for the Experimental group from pretest (*M* = 176.02, S*D* = 21.770) to posttest (*M* = 178.61, S*D* = 22.61), as seen in Table 30 and 31 (*t*(53) = -1.516, *p* = .136). There was a statistically significant difference for the Control group from pretest (*M* = 170.59, S*D* = 23.10) to posttest (*M* = 162.41, S*D* = 22.09), as seen in Table 30 and 31 (*t*(38) = 2.145, *p* = .038). There was not a statistically significant difference for both (Experimental and Control) groups from pretest (*M* = 173.74, S*D* = 22.72) to posttest (*M* = 172.40, S*D* = 23.85), as seen in Table 30 and 31 (*t*(93) = .592, *p* = .540). Cohen's *d* = .343.

Table 31

Paired t-Test for Pretest and Posttest Mathematics Attitude for Experimental, Control, and Both Groups

							95% Confidence Interval for Difference		
Variables	*n*	Mean	SD(*P*)	SEM	*T*	df	Sig (2-tailed)	Lower	Upper
Pretest Posttest Experimental	54	-3.59	17.418	2.370	-1.516	53	.136	-8.35	1.16
Pretest Posttest Control	39	8.18	23.818	3.814	2.145	38	.038	.46	15.90
Pretest Posttest Both	93	1.34	21.052	2.183	.616	92	.540	-2.99	5.68

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MA given to the Experimental group and Control group. Scatterplots suggest a positive correlation between the pretest and posttest MA for the four categories, as seen in Figures 26 through 40. Scatterplots of the entire sample including Experimental, Control, and both (Experimental and Control) groups divided into the four components.

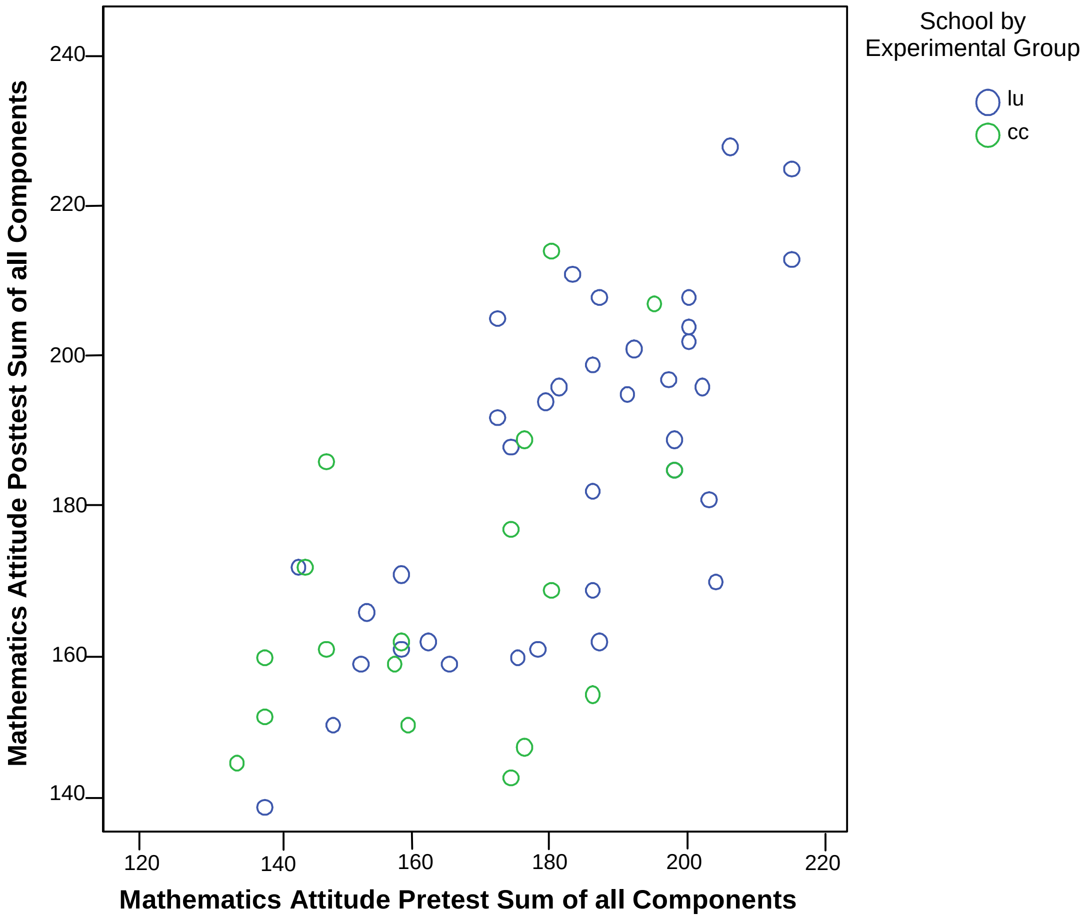

Figure 26. Scatterplot of Pretest Mathematics Attitude (47 Questions) as Independent Variable and Posttest Mathematics Attitude (47 Questions) as Dependent Variable of Experimental Group Only.

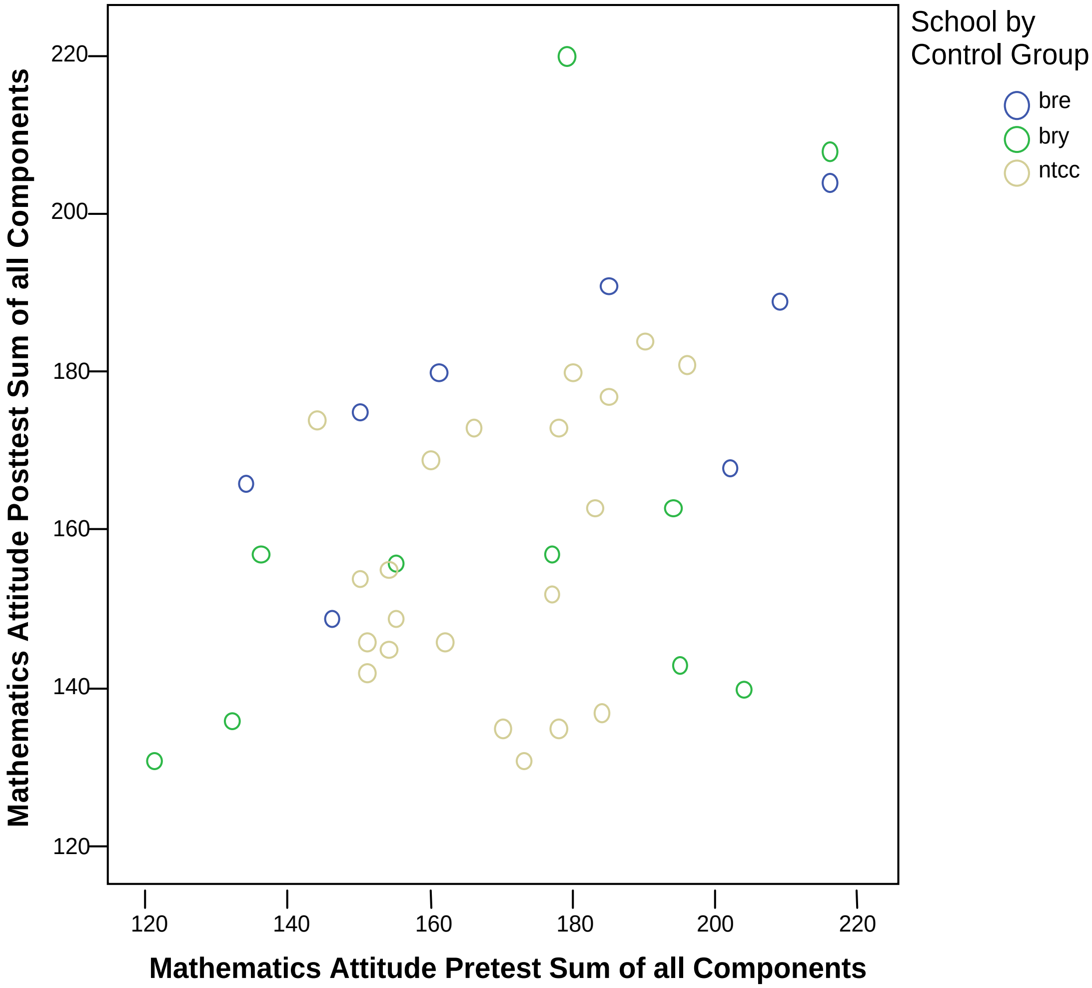

Figure 27. Scatterplot of Pretest Mathematics Attitude (47 Questions) as Independent Variable and Posttest Mathematics Attitude (47 Questions) as Dependent Variable of Control Group Only.

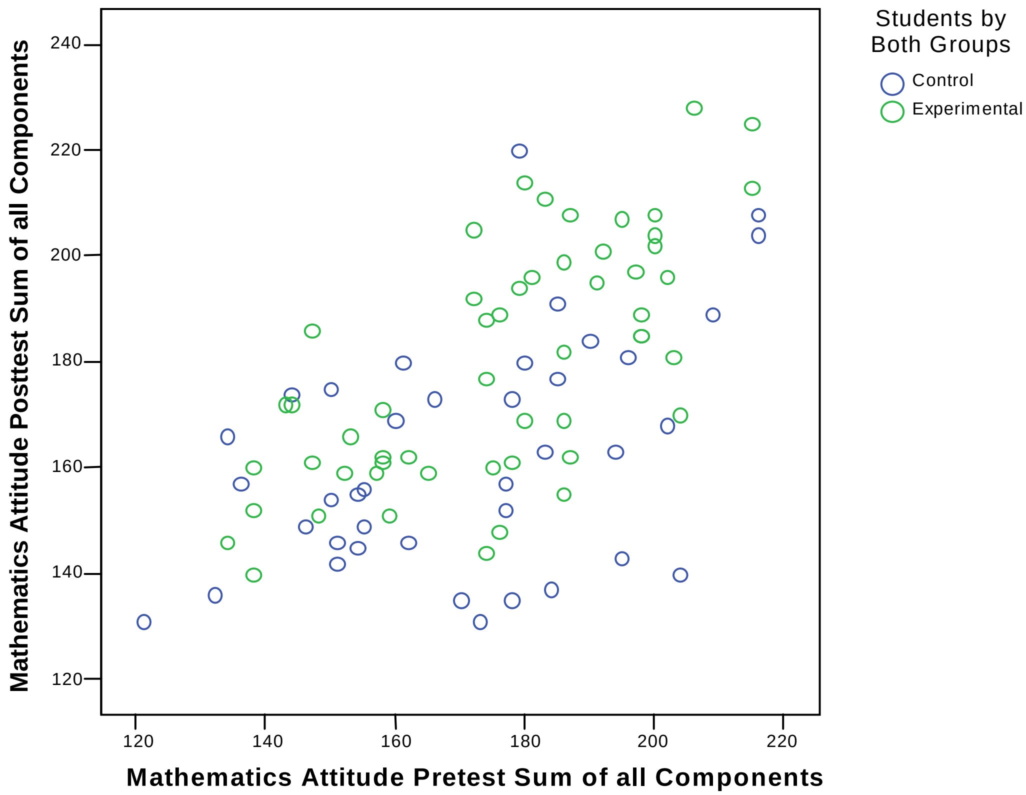

Figure 28. Scatterplot of Pretest Mathematics Attitude (47 Questions) as Independent Variable and Posttest Mathematics Attitude (47 Questions) as Dependent Variable of Both Groups.

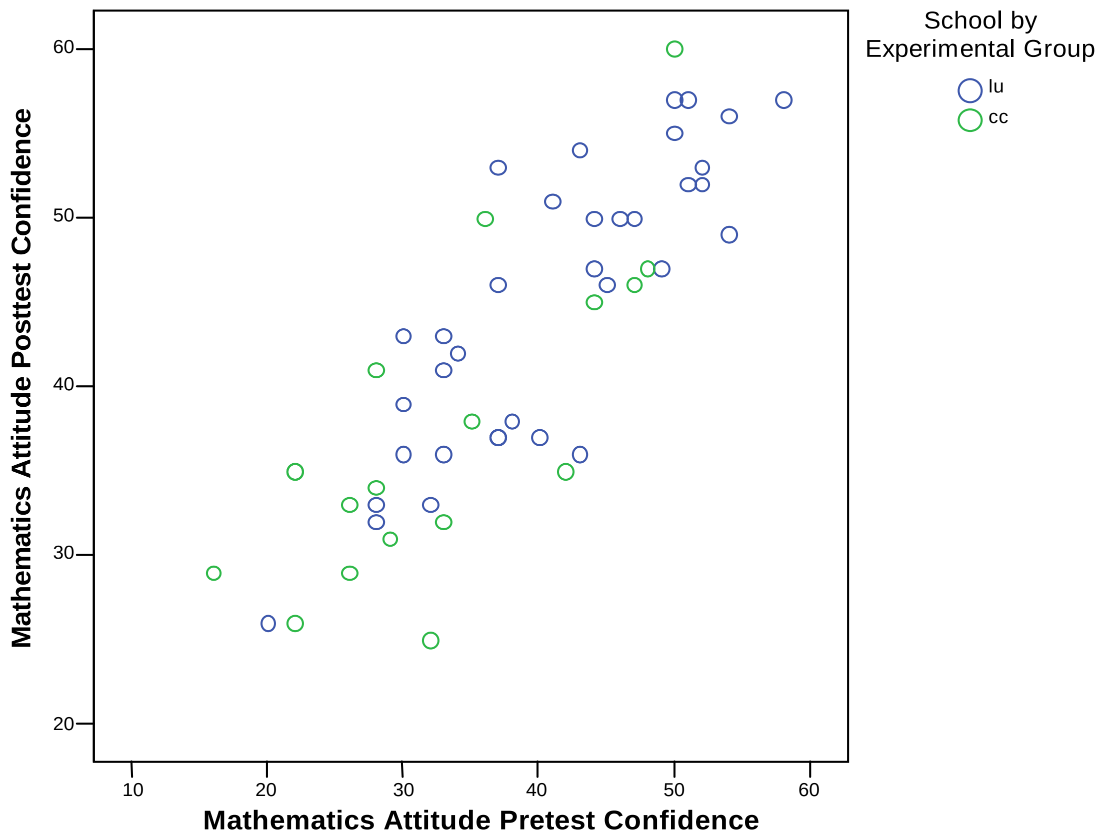

Figure 29. Scatterplot of Pretest Mathematics Attitude Confidence (12 Questions) as Independent Variable and Posttest Mathematics Attitude Confidence (12 Questions) as Dependent Variable of Experimental Group Only.

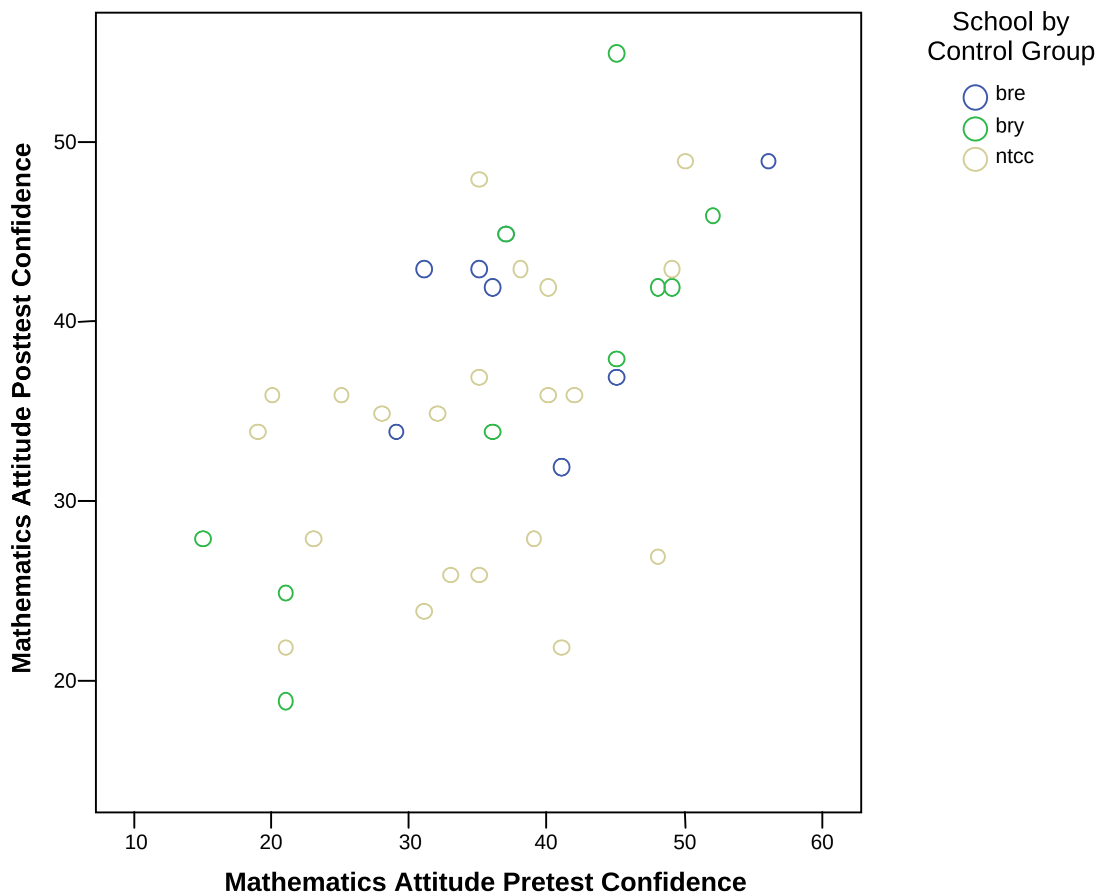

Figure 30. Scatterplot of Pretest Mathematics Attitude Confidence (12 Questions) as Independent Variable and Posttest Mathematics Attitude Confidence (12 Questions) as Dependent Variable of Control Group Only.

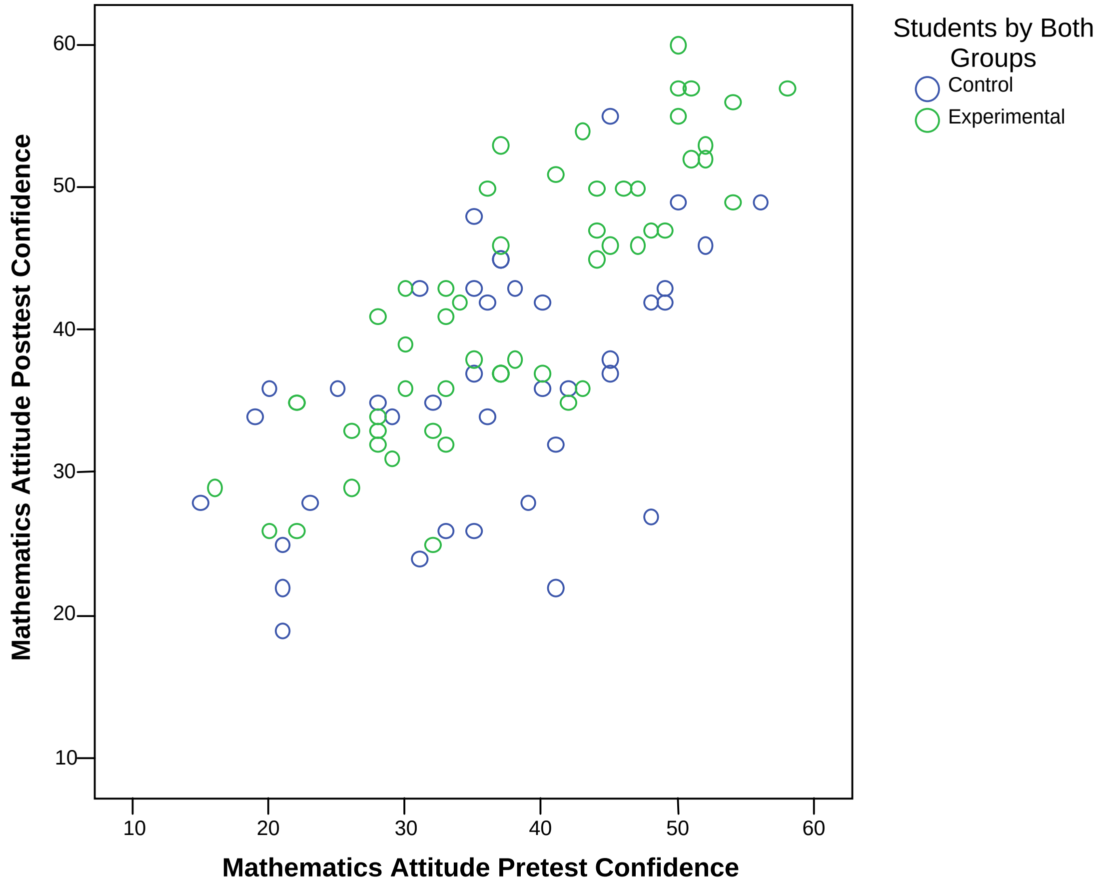

Figure 31. Scatterplot of Pretest Mathematics Attitude Confidence (12 Questions) as Independent Variable and Posttest Mathematics Attitude Confidence (12 Questions) as Dependent Variable of Both Groups.

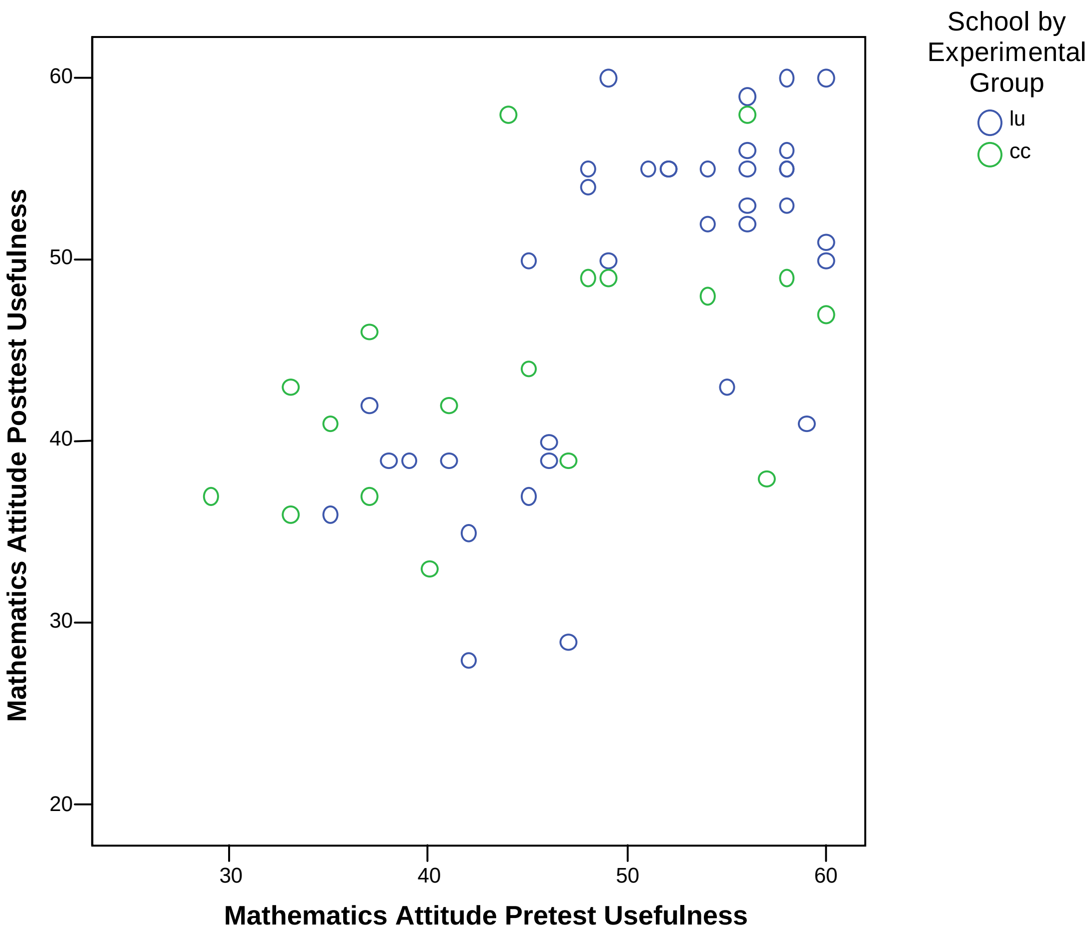

Figure 32. Scatterplot of Pretest Mathematics Attitude Usefulness Component (12 Questions) as Independent Variable and Posttest Mathematics Attitude Usefulness Component (12 Questions) as Dependent Variable of Experimental Group Only.

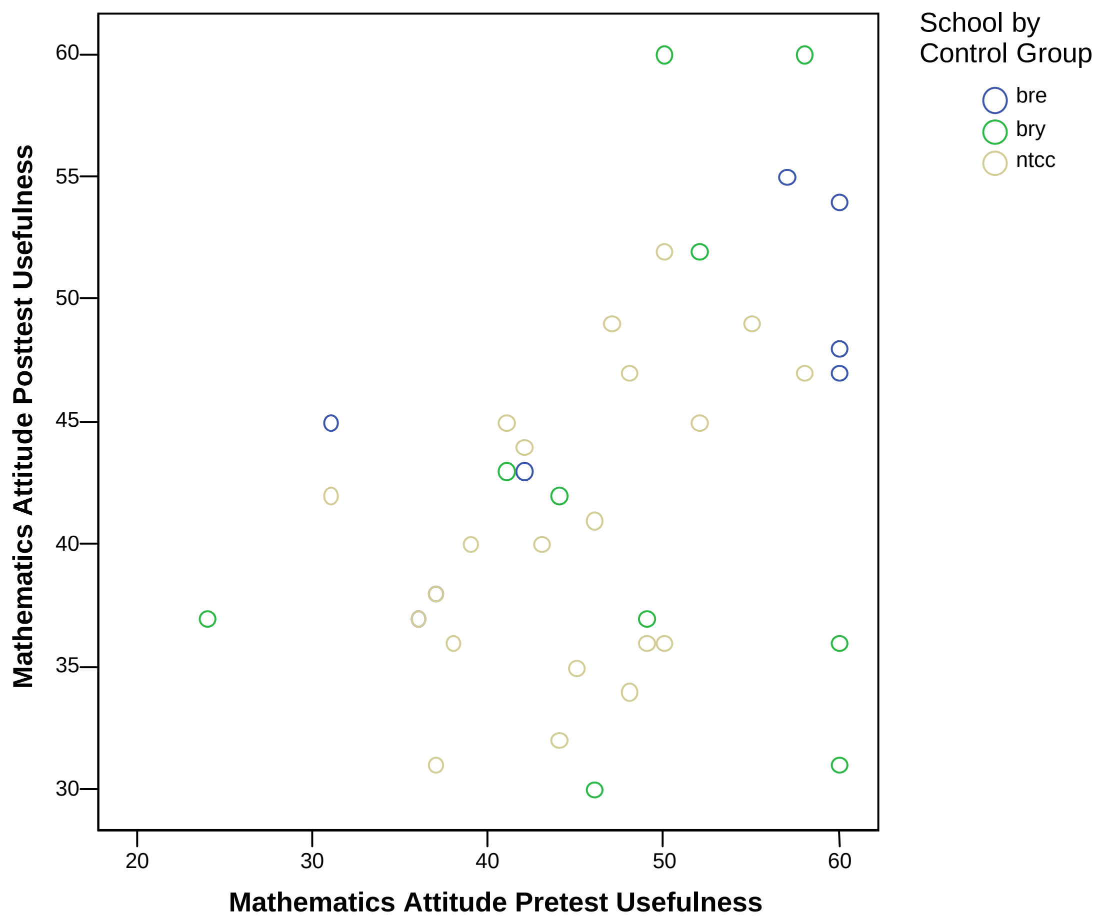

Figure 33. Scatterplot of Pretest Mathematics Attitude Usefulness Component (12 Questions) as Independent Variable and Posttest Mathematics Attitude Usefulness Component (12 Questions) as Dependent Variable of Control Group Only.

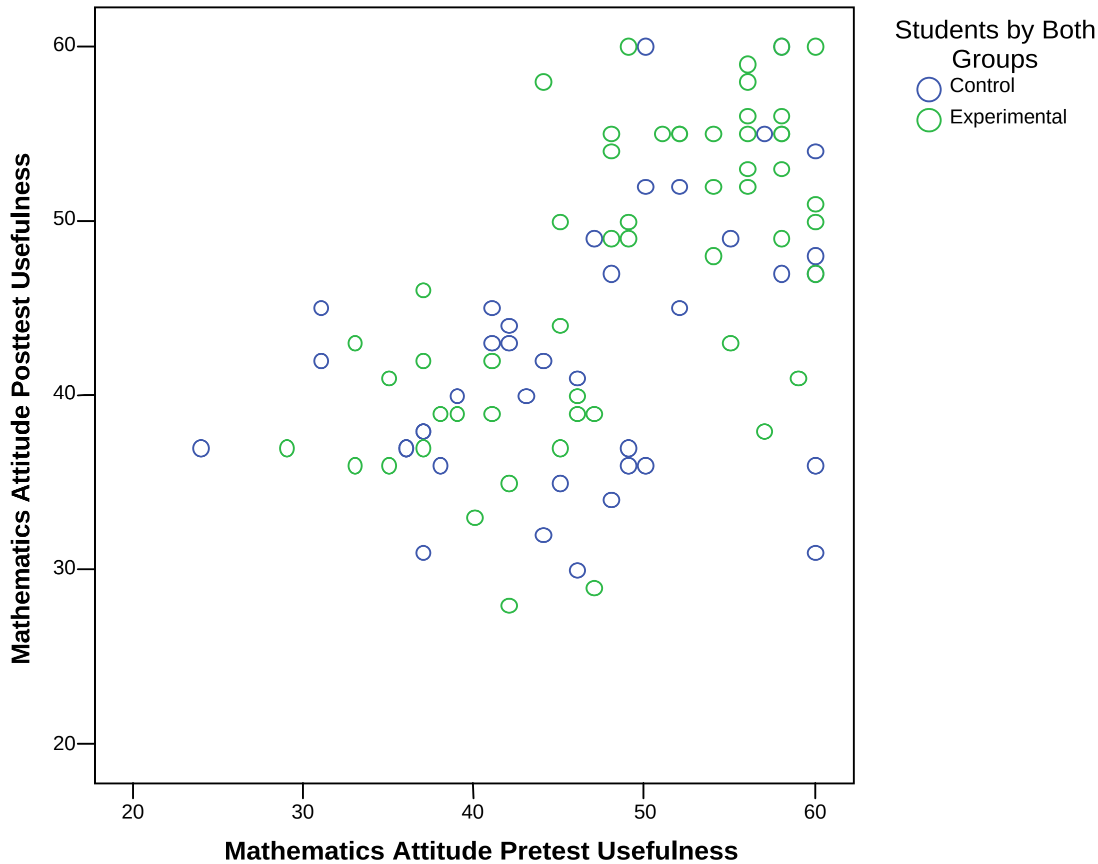

Figure 34. Scatterplot of Pretest Mathematics Attitude Usefulness Component (12 Questions) as Independent Variable and Posttest Mathematics Attitude Usefulness Component (12 Questions) as Dependent Variable of Both Groups.

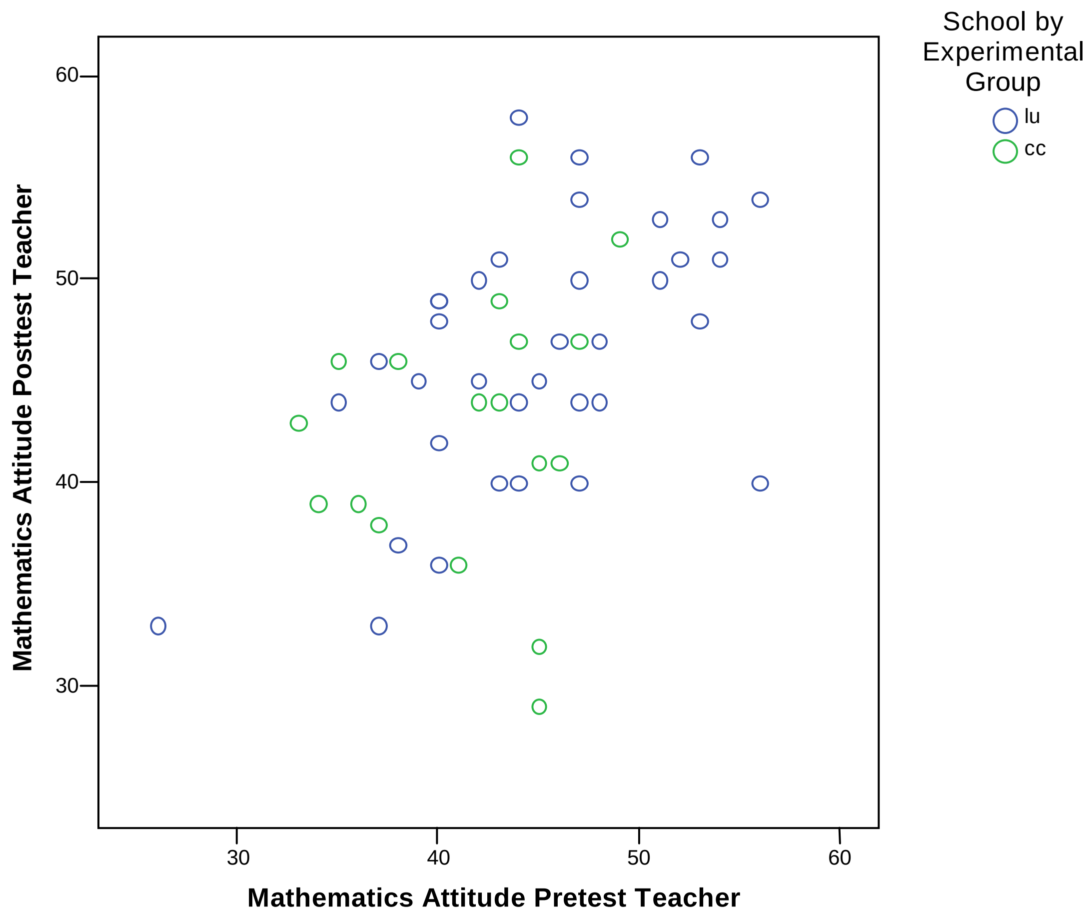

Figure 35. Scatterplot of Pretest Mathematics Attitude Teacher Component (12 Questions) as Independent Variable and Posttest Mathematics Attitude Teacher Component (12 Questions) as Dependent Variable of Experimental Group Only.

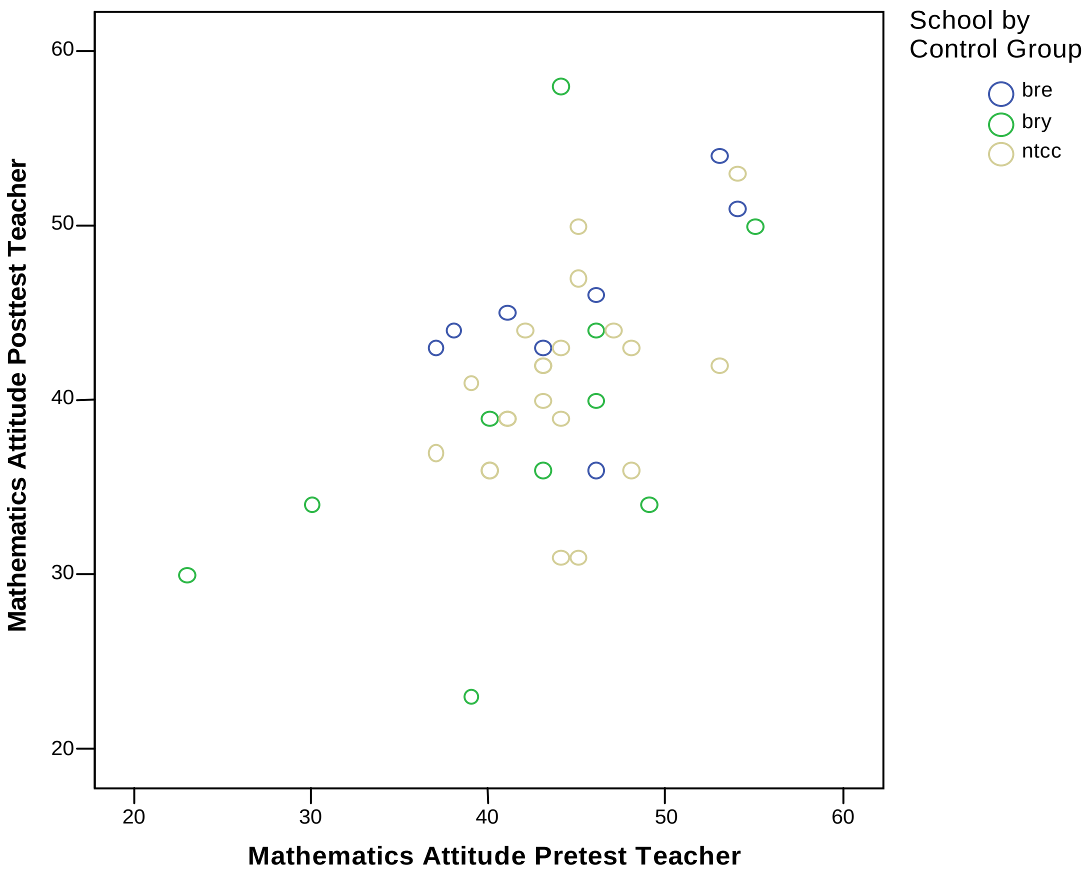

Figure 36. Scatterplot of Pretest Mathematics Attitude Teacher Component (12 Questions) as Independent Variable and Posttest Mathematics Attitude Teacher Component (12 Questions) as Dependent Variable of Control Group Only.

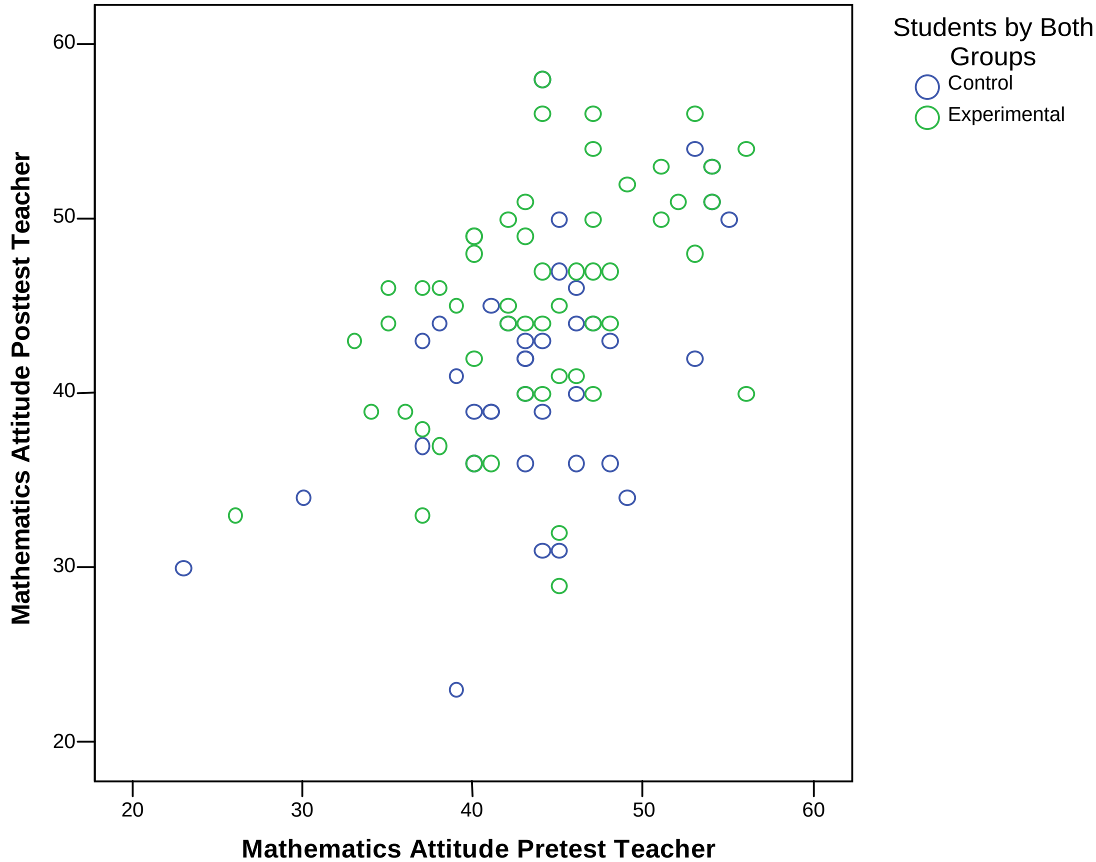

Figure 37. Scatterplot of Pretest Mathematics Attitude Teacher Component (12 Questions) as Independent Variable and Posttest Mathematics Attitude Teacher Component (12 Questions) as Dependent Variable of Both Groups.

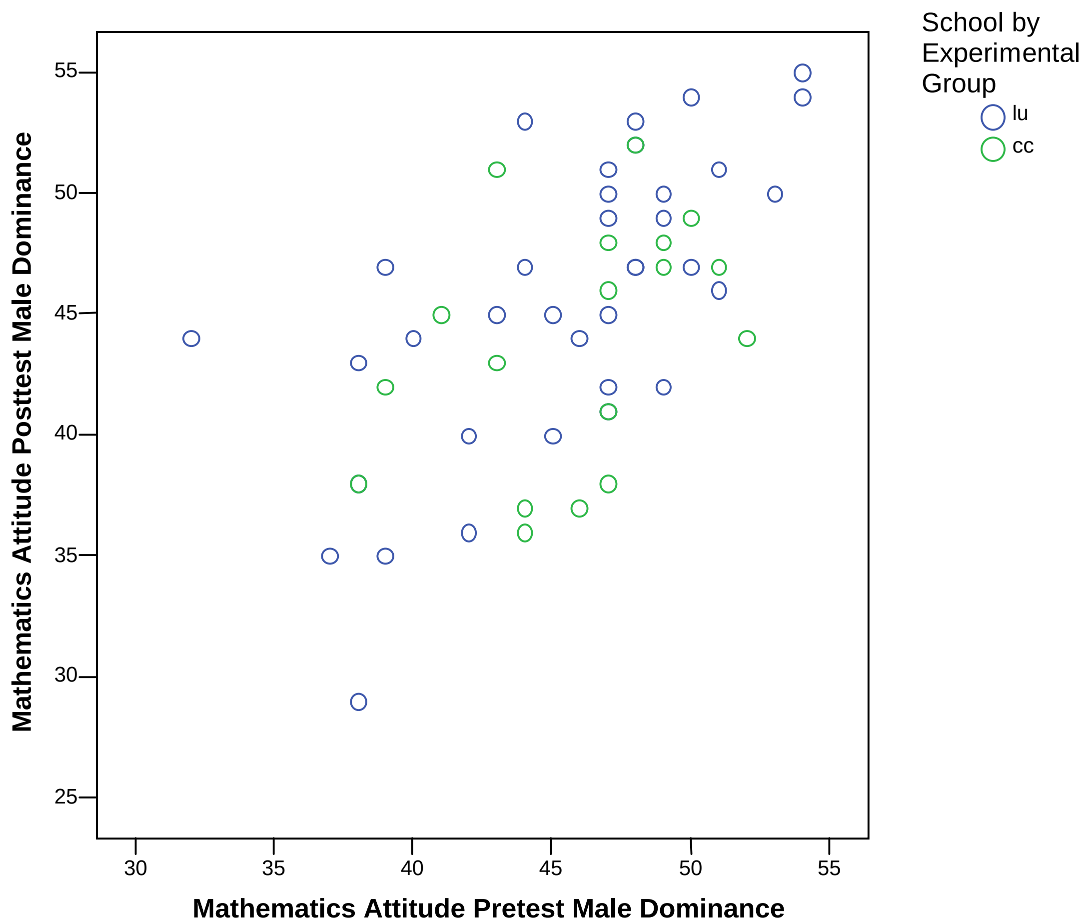

Figure 38. Scatterplot of Pretest Mathematics Attitude Male Dominance Component (11 Questions) as Independent Variable and Posttest Mathematics Attitude Male Dominance Component (11 Questions) as Dependent Variable of Experimental Group Only.

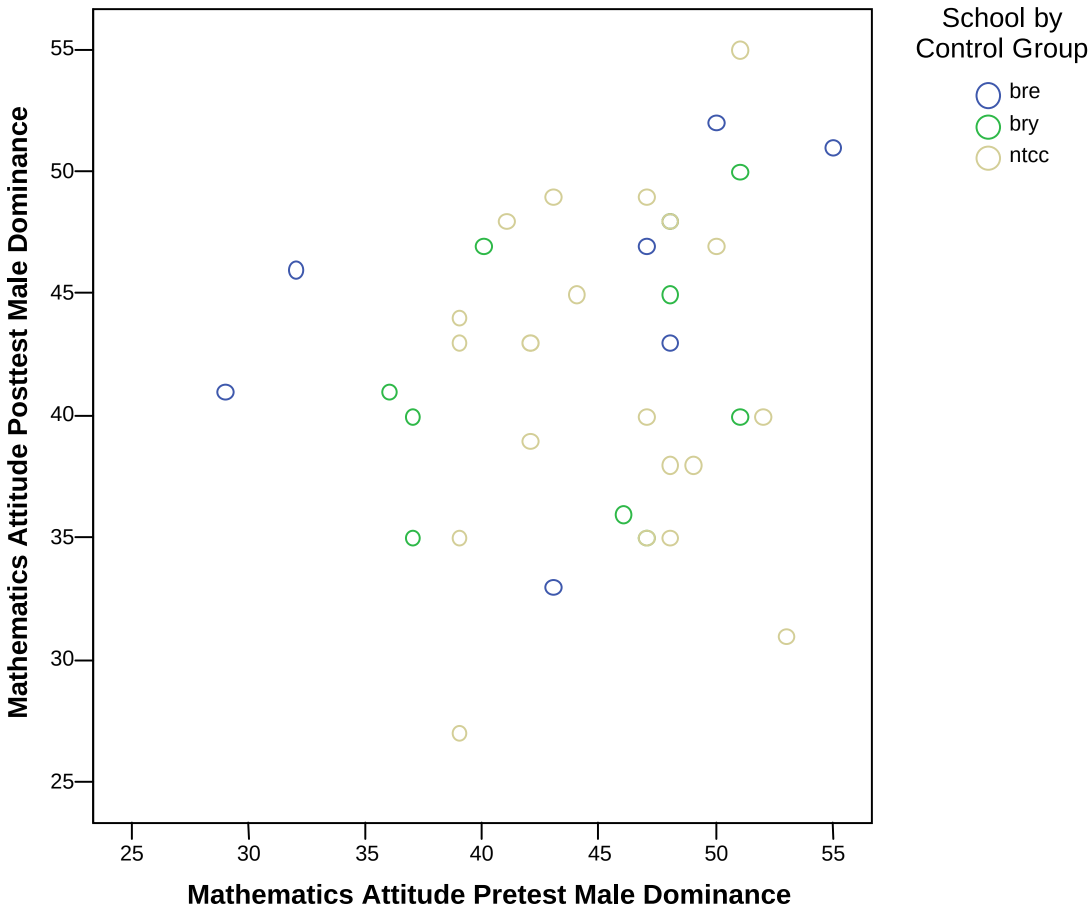

Figure 39. Scatterplot of Pretest Mathematics Attitude Male Dominance Component (11 Questions) as Independent Variable and Posttest Mathematics Attitude Male Dominance Component (11 Questions) as Dependent Variable of Control Group Only.

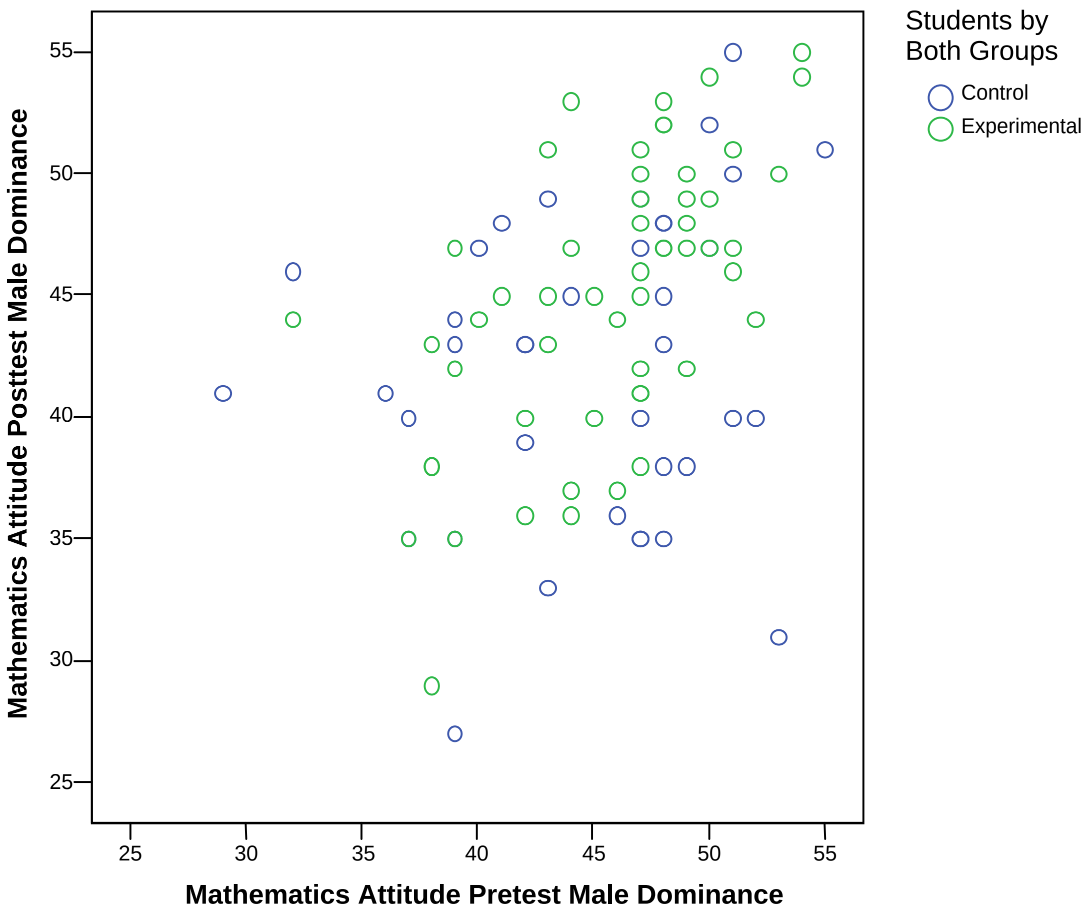

Figure 40. Scatterplot of Pretest Mathematics Attitude Male Dominance Component (11 Questions) as Independent Variable and Posttest Mathematics Attitude Male Dominance Component (11 Questions) as Dependent Variable of Both Groups.

The relationship between MA pretest and posttest was investigated using Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables (r = .693, n =54, p < .001) with higher scores on the pretest associated with higher scores on the posttest for the Experimental group shown in Table 32.There was a medium positive correlation between the variables (r = .466, n = 39, p < .001), shown in

Table 33, with higher scores on the pretest associated with higher scores on the posttest for the Control group. There was a medium positive correlation between both (Experimental and Control) groups between the two variables ($r = .592$, $n = 93$, $p < .001$), shown in Table 34, with higher scores on the pretest associated with higher scores on the posttest. Boxplots illustrated in Figures 41 through 50 can be examined for further information.

Table 32

Pearson Correlations Between Pretest and Posttest Mathematics Attitude for Experimental Group Only

Measures	1	2	3	4	5	6
1 MAPRE	1	.693**	.818**	774**	.822**	.324*
2 MAPOST	.693**	1	.655**	.490**	.548**	.131
3 MAC	.818**	.655**	1	.593*	.489**	-.019
4 MAT	.774**	.492*	.563**	1	.520**	.087
5 MAU	.822**	.548**	.489**	.520**	1	.223
6 MAM	.324*	.131	-.019	.087	.223	1

N = 54. MAPRE = Mathematics Attitude Pretest; MAC = Mathematics Attitude Confidence Component; MAT = Mathematics Attitude Teacher Component; MAU = Mathematics Attitude Usefulness Component; MAM = Mathematics Attitude Male Dominance Component; MAPOST = Mathematics Attitude Posttest. ** $p < 0.01$,
* $p < 0.05$

Table 33

Pearson Correlations Between Pretest and Posttest Mathematics Attitude for Control Group Only

Measures	1	2	3	4	5	6
1 MAPRE	1	.466**	.811**	.715**	.833	.584
2 MAPOST	.466**	1	.422**	.402**	.384*	.117
3 MAC	.811**	.422**	1	.363*	.597**	.234
4 MAT	.715**	.402*	.363	1	.471**	.495
5 MAU	.833**	.384*	.597**	.471**	1	.276
6 MAM	.584**	.117	.234	.495**	.276	1

N = 39. MAPRE = Mathematics Attitude Pretest; MAC = Mathematics Attitude Confidence Component; MAT = Mathematics Attitude Teacher Component; MAU = Mathematics Attitude Usefulness Component; MAM = Mathematics Attitude Male Dominance Component; MAPOST = Mathematics Attitude Posttest. ** $p < 0.01$, * $p < 0.05$

Table 34

Pearson Correlations Between Pretest and Posttest Mathematics Attitude for Both Groups

Measures	1	2	3	4	5	6
1 MAPRE	1	.816**	.744**	.829**	.456*	.592**
2 MAC	.816**	1	.478**	.542**	.107	.555**
3 MAT	.744**	.478**	1	.496*	.277**	.430**
4 MAU	.829**	.542**	.496**	1	.256**	.490**
5 MAM	.456**	.107	.277**	.256*	1	.145
6 MAPOST	.592**	.555**	.430**	.490**	.145	1

N = 93. MAPRE = Mathematics Attitude Pretest; MAC = Mathematics Attitude Confidence Component; MAT = Mathematics Attitude Teacher Component; MAU = Mathematics Attitude Usefulness Component; MAM = Mathematics Attitude Male Dominance Component; MAPOST = Mathematics Attitude Posttest. ** $p < 0.01$, * $p < 0.05$

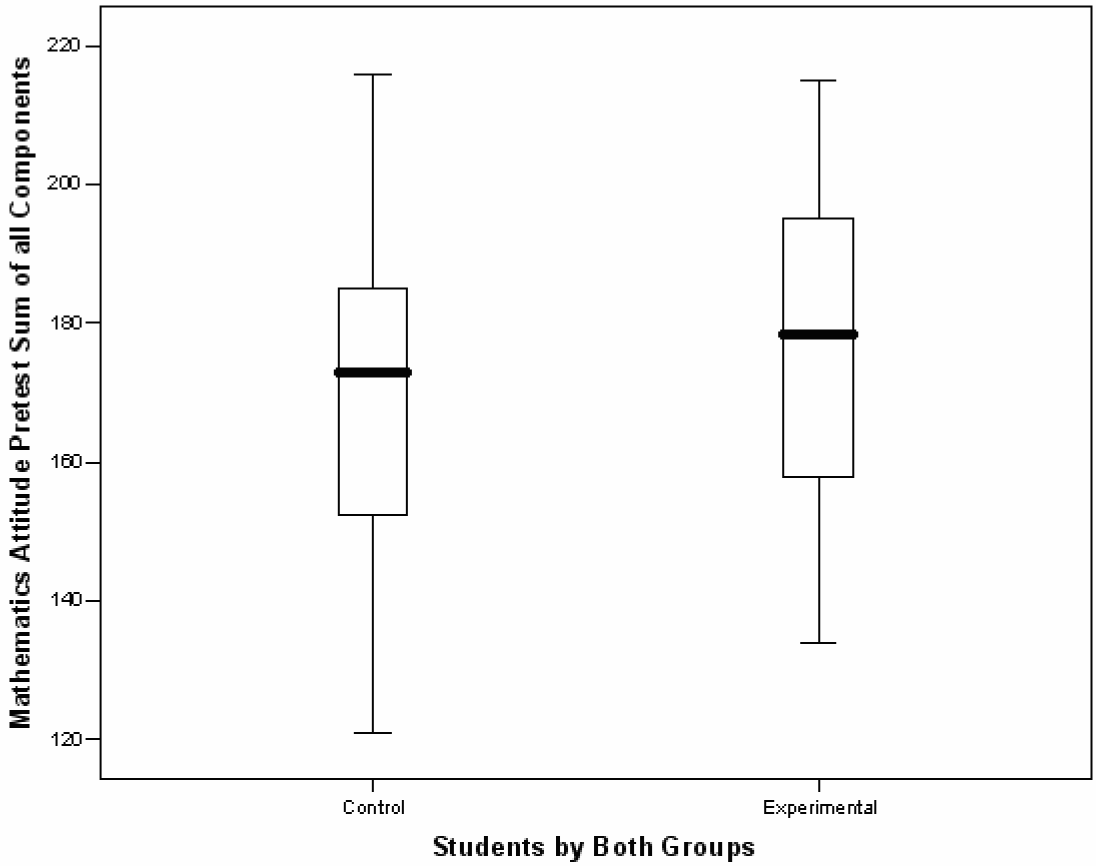

Figure 41. Boxplots of Mathematics Attitude Pretest by Experimental and Control Groups for all Four Components.

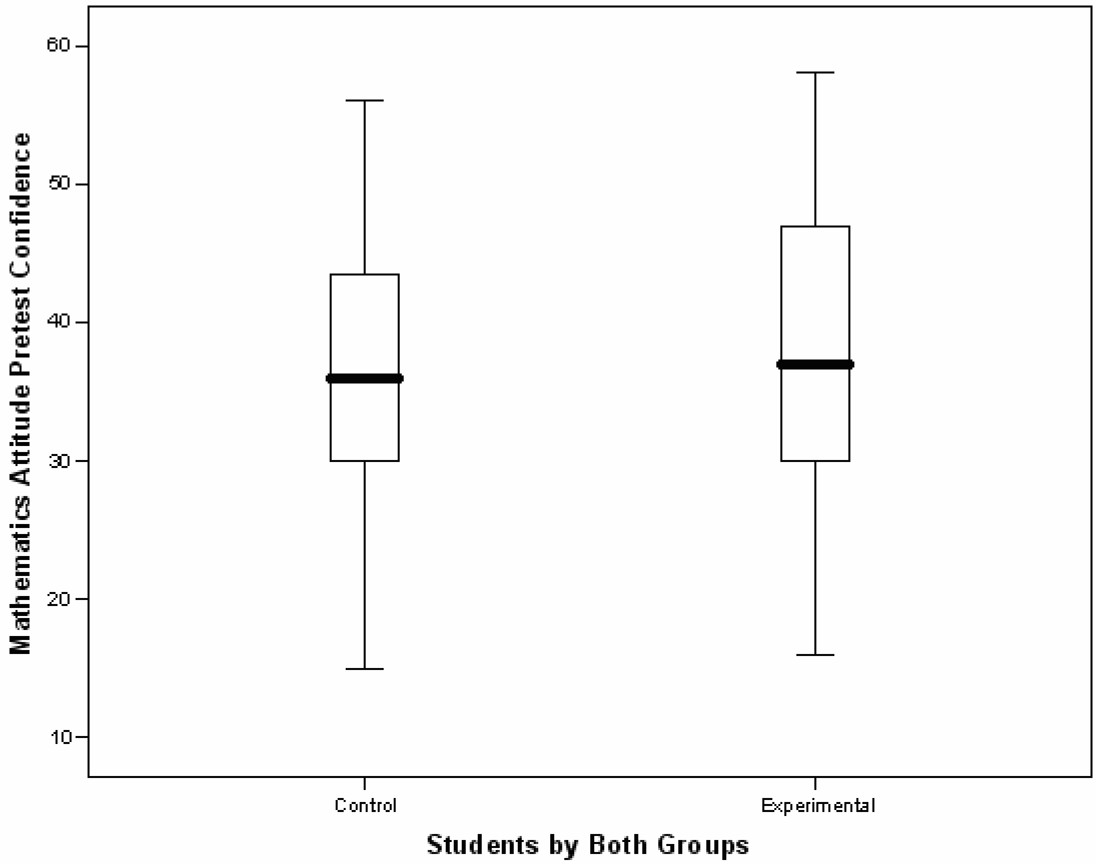

Figure 42. Boxplots of Mathematics Attitude Pretest Confidence Component by Experimental and Control Groups.

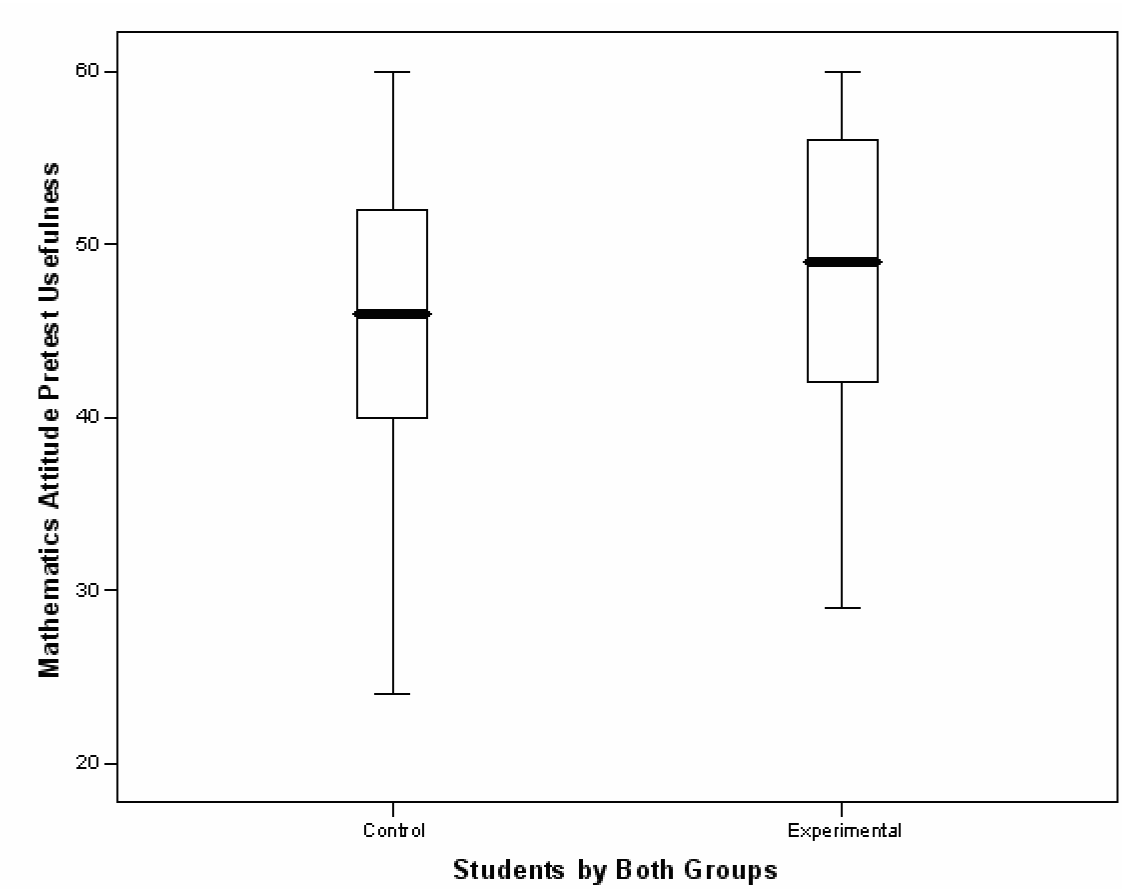

Figure 43. Boxplots of Mathematics Attitude Pretest Usefulness Component by Experimental and Control Groups.

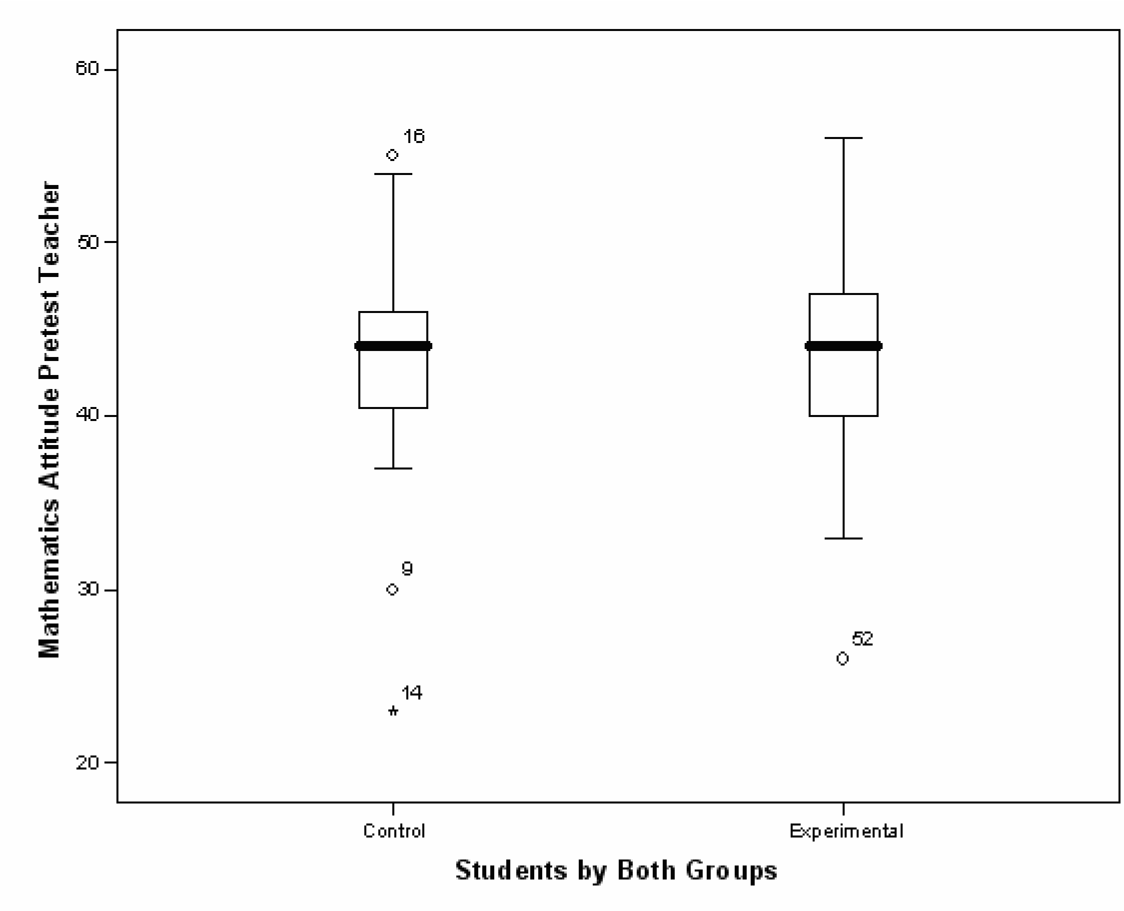

Figure 44. Boxplots of Mathematics Attitude Pretest Teacher Component by Experimental and Control Groups.

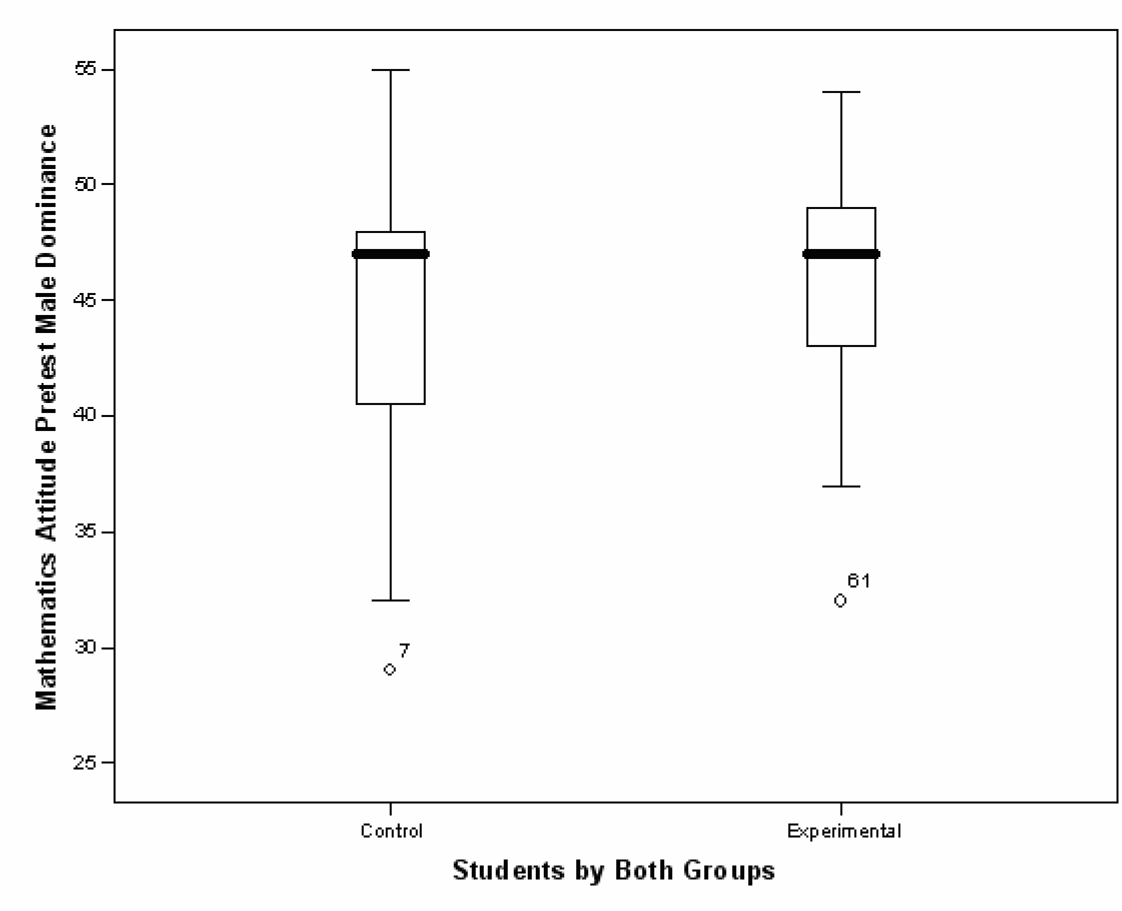

Figure 45. Boxplots of Mathematics Attitude Pretest Male Dominance Component by Experimental and Control Groups.

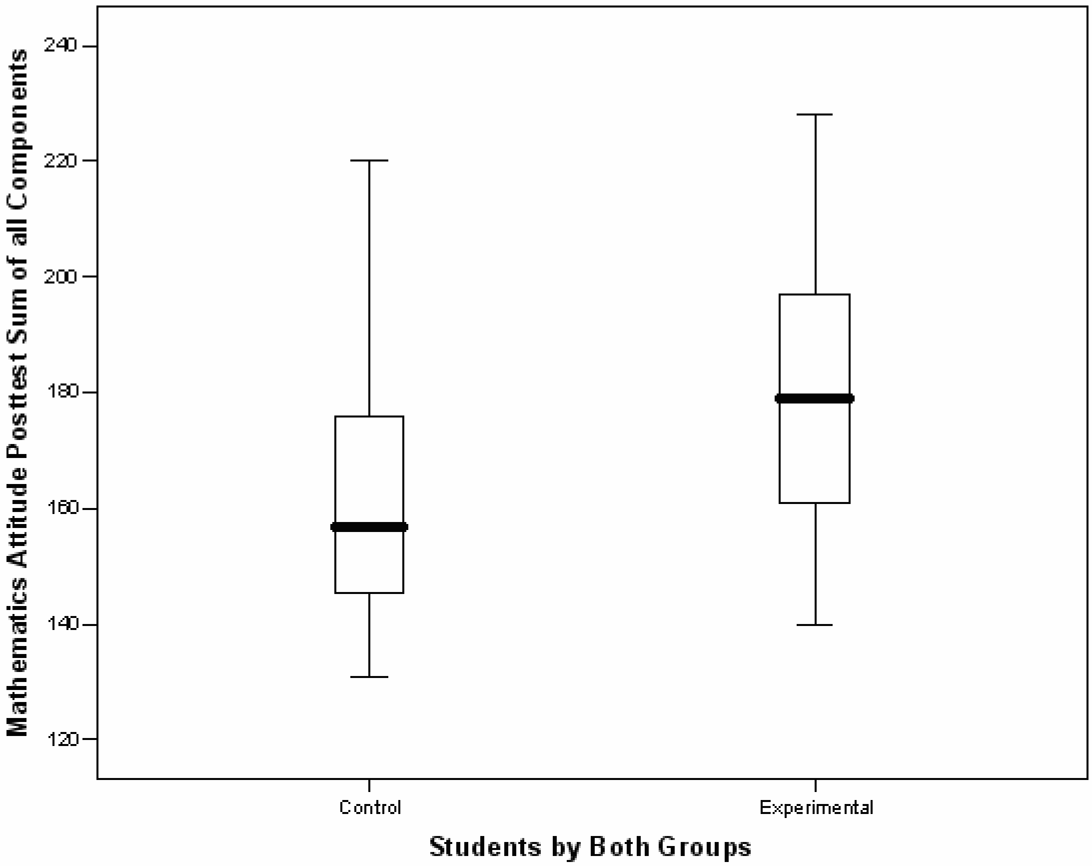

Figure 46. Boxplots of Mathematics Attitude Posttest For All Four Components by Experimental and Control Groups.

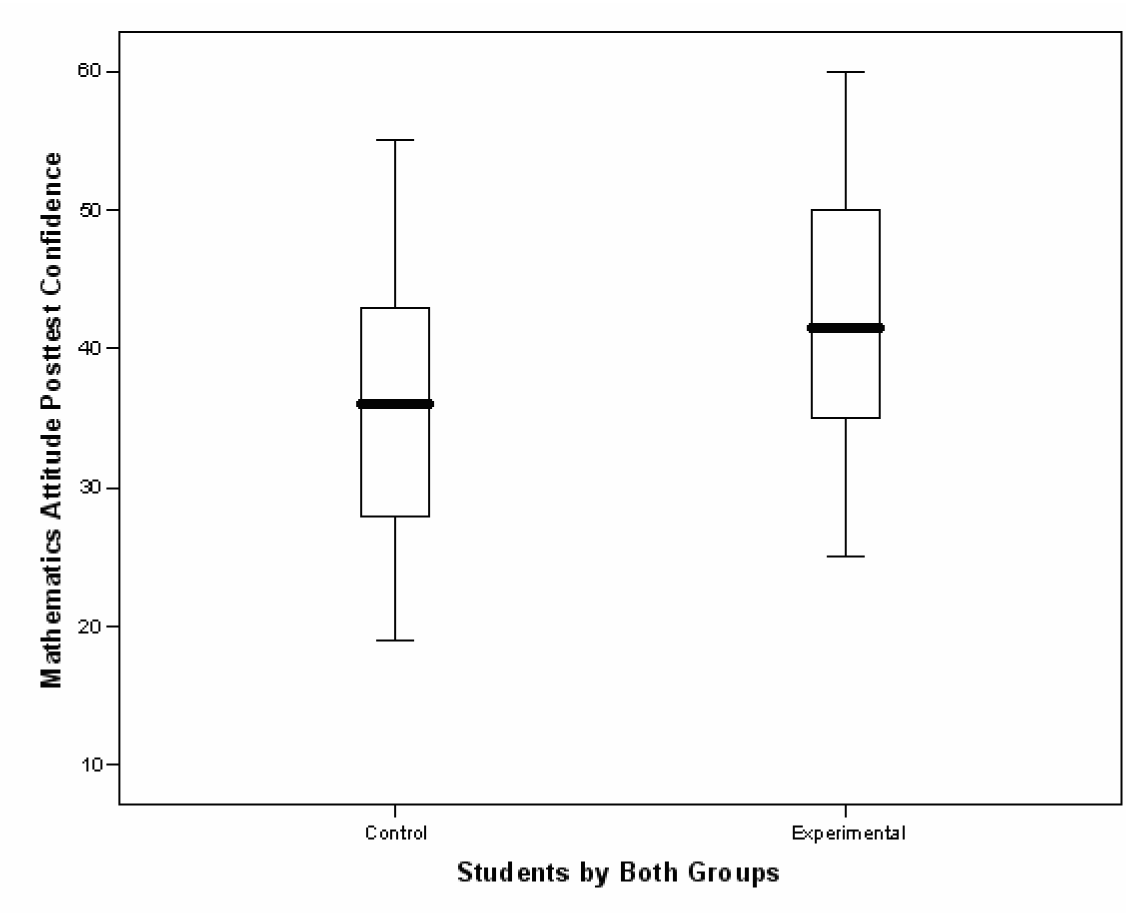

Figure 47. Boxplots of Mathematics Attitude Posttest Confidence Component by Experimental and Control Groups.

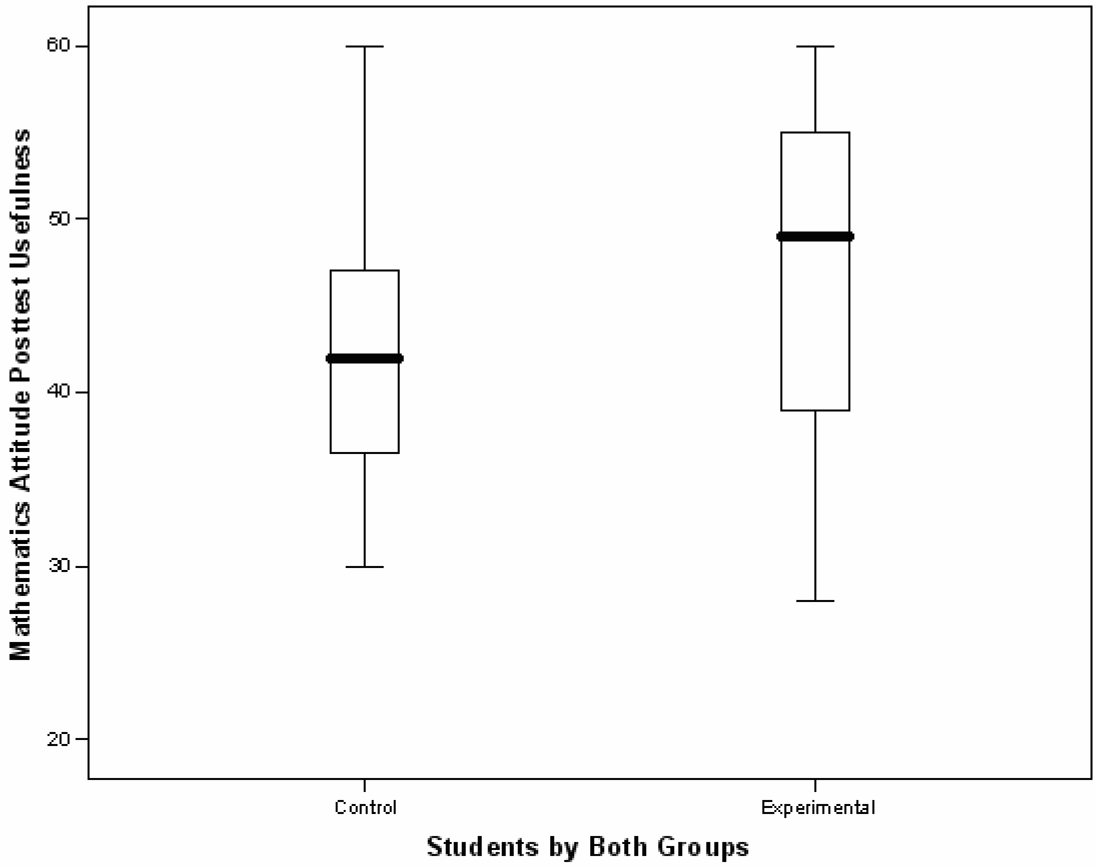

Figure 48. Boxplots of Mathematics Attitude Posttest Usefulness Component by Experimental and Control Groups.

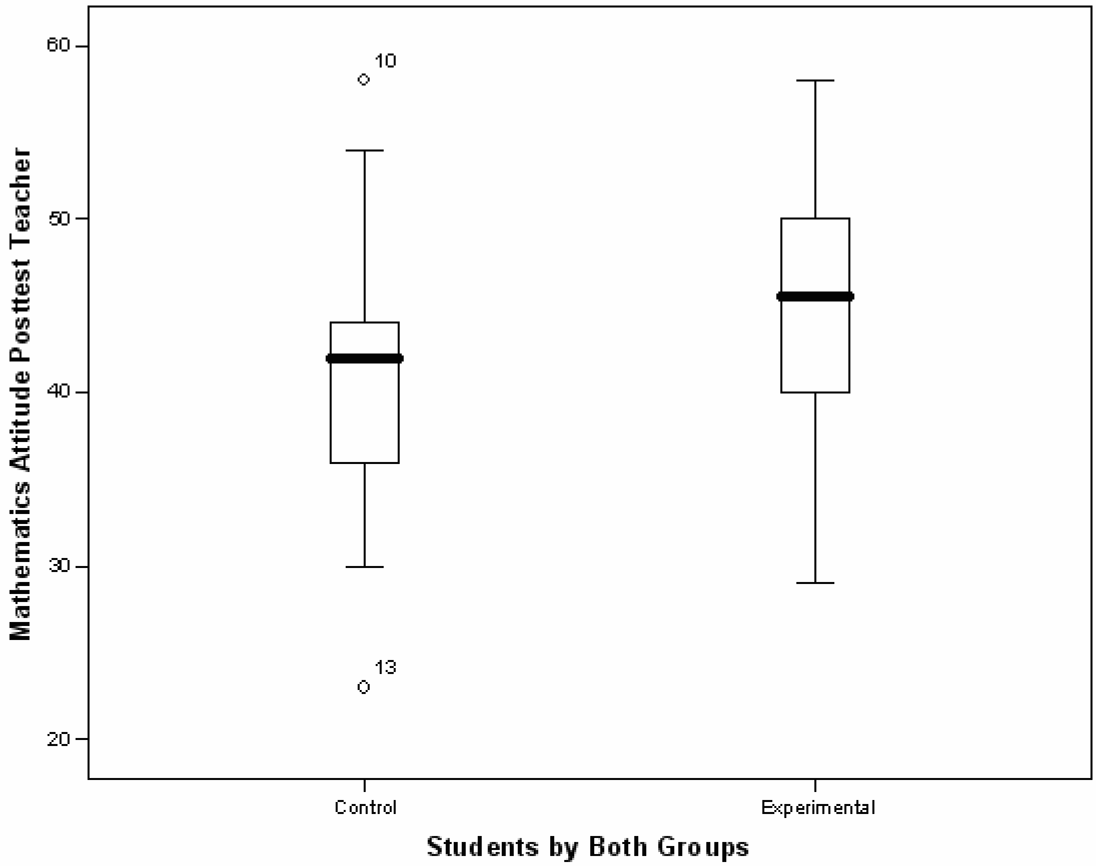

Figure 49. Boxplots of Mathematics Attitude Posttest Teacher Component by Experimental and Control Groups.

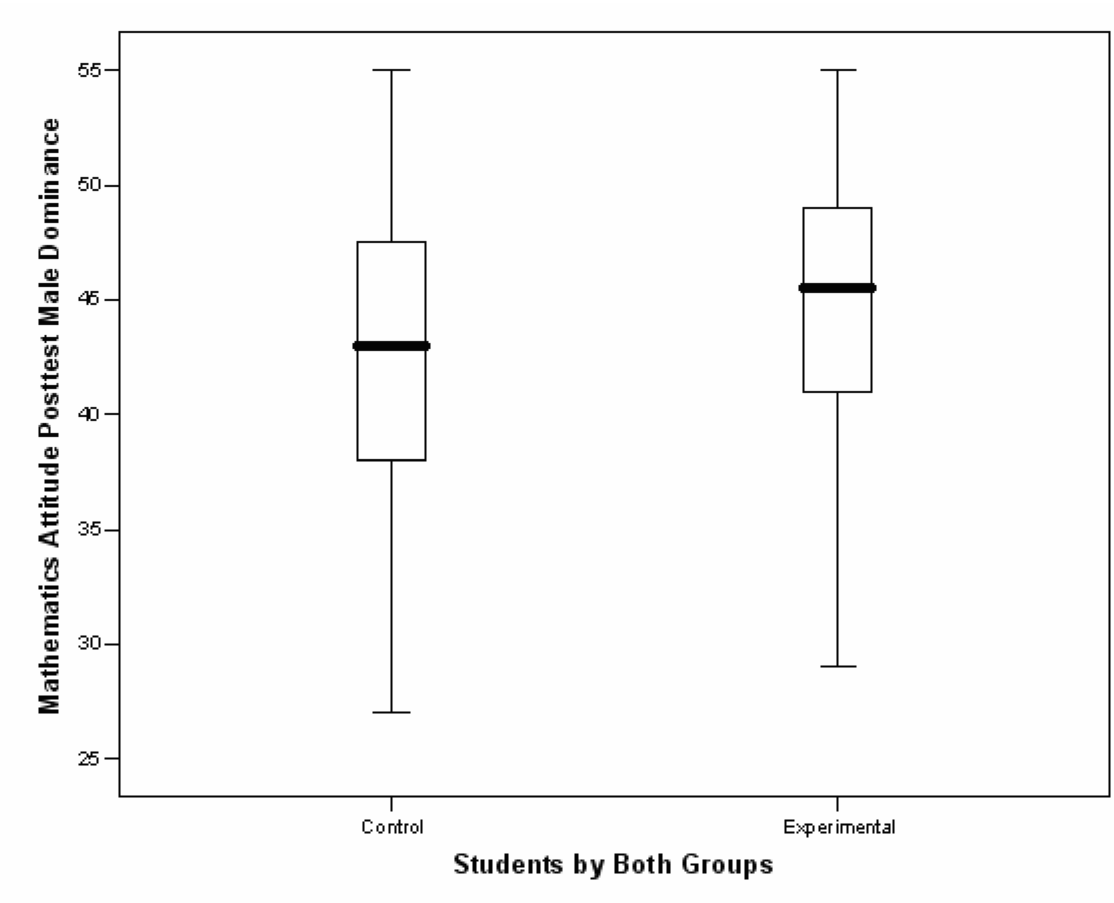

Figure 50. Boxplots of Mathematics Attitude Posttest Male Dominance Component by Experimental and Control Groups.

A paired-samples *t*-test was conducted to evaluate the impact of the intervention on students' scores on the four components of the MA (MAC, MAT, MAU, and MAM). Descriptive statistics are presented in Table 35. There was not a statistically significant difference for the Experimental and Control groups from pretest (M = 173.74, SD = 22.72) to posttest (M = 172.40, SD = 23.852), as seen in Table 36 (t(93) = .592, p = .540). There was not a statistically significant difference for the Experimental group from pretest (M = 176.02, SD = 21.77) to posttest (M = 178.61, SD = 22.61), as seen in Table 36 ($t(53) = -1.516$, $p = .136$). There was a statistically significant difference for the Control group from pretest (M = 170.59, SD = 23.91) to posttest (M = 162.41, SD = 22.09), as seen in Table 36 ($t(38) = 2.145$, $p = .038$). Examining the means shows the slope of MA pretest and posttest Confidence Experimental (m=-4.17), MA pretest and posttest Confidence Control (m=-.23), MA pretest and posttest Teacher Experimental (m=-1.46), MA pretest and posttest Teacher Control (m=2.41), MA pretest and posttest Usefulness Experimental (m=1.67), MA pretest and posttest Usefulness Control (m=3.90), MA pretest and posttest Male Dominance Experimental (m=.59), and MA pretest and posttest Male Dominance Control (m=2.38), as seen in Figure 51 and 52.

Table 35

Descriptive Statistics of Pretest and Posttest of Mathematics Attitude (47 Questions), Confidence (12 Questions), Teacher (12 Questions), Usefulness (12 Questions), and Male Dominance (11 Questions) Divided into Experimental and Control Groups

Students by Experimental and Control groups		Pairs	Mean	*N*	Std. Deviation	Std. Error Mean
Control	Pair 1	Math Attitude Pretest Sum	170.59	39	23.909	3.828
		Math Attitude Posttest Sum	162.41	39	22.093	3.538
	Pair 2	Math Attitude Pretest Confidence	35.97	39	10.256	1.642
		Math Attitude Posttest Confidence	36.21	39	8.733	1.398
	Pair 3	Math Attitude Pretest Teacher	43.56	39	6.210	.994
		Math Attitude Posttest Teacher	41.15	39	7.066	1.131

Table 35 (continued)

Students by Experimental and Control groups		Pairs	Mean	*N*	Std. Deviation	Std. Error Mean
	Pair 4	Math Attitude Pretest Usefulness	46.23	39	9.184	1.471
		Math Attitude Posttest Usefulness	42.33	39	7.750	1.241
	Pair 5	Math Attitude Pretest Male Dominance	44.69	39	5.899	.945
		Math Attitude Posttest Male Dominance	42.31	39	6.358	1.018
Experimental	Pair 1	Math Attitude Pretest Sum	176.02	54	21.770	2.963
		Math Attitude Posttest Sum	179.61	54	22.610	3.077
	Pair 2	Math Attitude Pretest Confidence	38.04	54	10.187	1.386
		Math Attitude Posttest Confidence	42.20	54	9.349	1.272
	Pair 3	Math Attitude Pretest Teacher	43.76	54	6.222	.847
		Math Attitude Posttest Teacher	45.22	54	6.655	.906
	Pair 4	Math Attitude Pretest Usefulness	48.65	54	8.600	1.170
		Math Attitude Posttest Usefulness	46.98	54	8.660	1.179
	Pair 5	Math Attitude Pretest Male Dominance	45.57	54	4.796	.653
		Math Attitude Posttest Male Dominance	44.98	54	5.797	.789

Table 36

Paired t-Test for Pretest and Posttest Mathematics Attitude for Experimental and Control Groups

								95% Confidence Interval for Difference	
Variables	*n*	Mean	SD(*P*)	SEM	*T*	Df	Sig (2-tailed)	Lower	Upper
MA Control									
Pretest Posttest Sum	39	8.18	23.818	3.814	2.145	38	.038	.46	15.90
Pretest Posttest Confidence	39	-.23	9.077	1.453	-.159	38	.875	-3.17	2.71
Pretest Posttest Teacher	39	2.41	6.504	1.041	2.314	38	.026	.30	4.52
Pretest Posttest Usefulness	39	3.90	9.313	1.491	2.614	38	.013	.88	6.92
Pretest Posttest Male Dominance	39	2.38	9.313	1.491	2.614	38	.061	-.12	4.89
MA Experimental									
Pretest Posttest Sum	54	-3.59	17.418	2.370	-1.516	53	.136	-8.35	1.16
Pretest Posttest Confidence	54	-4.17	5.653	.769	-5.417	53	.0005	-5.71	-2.62
Pretest Posttest Teacher	54	-1.46	6.575	.895	-1.635	53	.108	3.26	.33
Pretest Posttest Usefulness	54	1.67	7.343	.999	1.668	53	.101	-.34	3.67
Pretest Posttest Male Dominance	54	.59	4.847	.660	.898	53	.373	-.73	1.92

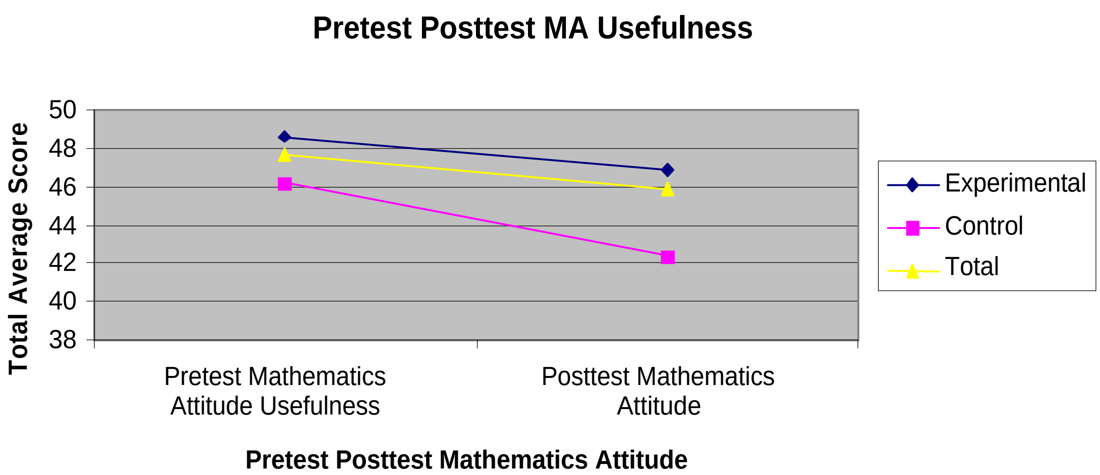

Figure 51. Line Graph of Experimental, Control, and Total of MA Usefulness Component.

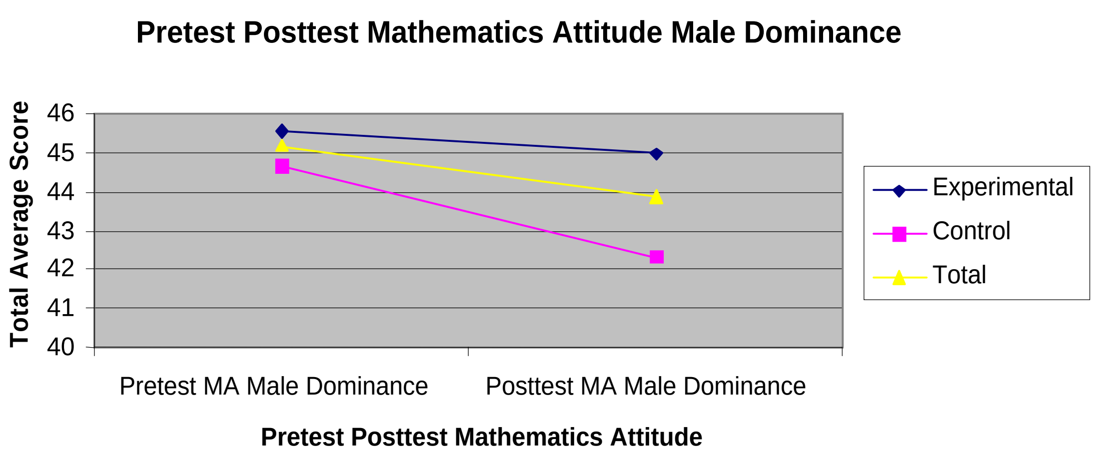

Figure 52. Line Graph of Experimental, Control, and Total of MA Male Dominance Component.

A MANOVA was conducted to test differences between Control (n = 39) and Experimental (n = 54) students on MA pretest and posttest divided into the four components: Confidence, Teacher, Usefulness, and Male Dominance. A MANOVA is used for analyses when there are two or more dependent variables. In this case, the dependent variables are MA pretest and posttest on the four components. This test was designed to measure perceived attitudes toward mathematics broken into the four components. Box's *M* test indicated the assumption of homogeneity of covariance matrices was met (p = .015). Statistically significant differences did exist between Control and Experimental groups of students on MA pretest and posttest for the four components (F(8,84) = 2.646891, p = .012), with a moderate effect size of (η^2 = .201).

Research Question VI

Is there differential performance between students who use ALEKS and Control group counterparts, and are there measurable differences one, two, and three years after completing the program?

A MANOVA was conducted to test differences between Control (n = 39) and Past Experimental (n = 29) students on the three tests, NATFYAT, MARS, and MA. Box's *M* test indicated the assumption of homogeneity of covariance matrices was met (p = .102). Statistically significant differences did not exist between Control and past Experimental groups of students on the three tests (F(3,64) = 1.89062, p = .140), with a moderate effect size of (η^2 = .08). Examining the univariate F-tests indicated that statistical significant differences only existed for the MA (F(1,66) = 4.91664, p = .030) and not the NATFYAT (F(1,66) = 1.49710, p = .225), or the MARS (F(1,66) = .65256, p

= .422). Table 36 presents the descriptive statistics for MA pretest and posttest for the Control and Past Experimental groups of students. Table 37 presents the descriptive statistics for NATFYAT for the Past Experimental and Control groups of students.

Table 37

Descriptive Statistics of NATFYAT Past Experimental and Control Groups

Variable	Students	*N*	Mean	SD	SEM
Algebra Test	Control	39	19.67	8.731	1.398
	Past	29	22.21	8.095	1.503
Mathematics Anxiety Rating Scale	Control	39	78.46	18.666	2.989
	Past	29	76.28	17.996	3.342
Mathematics Attitude Sum	Control	39	162.41	22.093	3.538
	Past	28	178.89	35.771	6.760

Interviews

Students who had been enrolled in an Intermediate Algebra class using ALEKS were contacted by e-mail, and were asked to participate in an interview. The interview was conducted with ten students that had taken an Intermediate Algebra course using ALEKS from the past three years. Appendix D contains the questions that were used for the interview. Students were asked the type of instruction they had prior coming to the university. All of the students' answers were the lecture method except for one student that had been home schooled. The home-schooled student's curriculum was set up on a self-paced lecture method. When asked what they liked about ALEKS, the responses were about the instruction: (a) self-paced, (b) immediate feedback, (c) great instructions with alternative instructions available, and accessibility: (i.e., assessments available when students were ready, could access ALEKS anywhere, and did not have to be in the lab at school). When asked what they did not like about ALEKS, the responses included: (a) “I don’t like how the assessments can set you so far behind,” (b) “I think they should test you only on things you did,” and (c) “I am a person who learns better from a teacher showing how to do it and explaining it to me one on one.” Students were also asked how they would compare ALEKS with other online classes that they had taken and none of the students interviewed had taken another class online.

In addition, students using ALEKS who knew they were not going to finish all of the objectives required asked to drop Intermediate Algebra using ALEKS. Students indicated they would be enrolling in another ALEKS Intermediate Algebra class because they believed they would fail if enrolled in a lecture class. The students then enrolled in the ALEKS Intermediate Algebra class the following semester. Because interviews were not conducted with the Control group, information about student drop rates was not available for the non-ALEKS group.

CHAPTER V

CONCLUSIONS

The future of American society and individuals depends on a solid education. The young person without a solid education will not see a very bright future. National Commission on Excellence in Education (NCEE) (1998) stated, “a good education is the great equalizer of American society” (p. 3). NCEE also noted, “Good post-secondary education has become absolutely indispensable for economic success, both for individuals and for American society” (NCEE, 1998, p. 2). Currently, students are kept in school for a certain number of years and excellence is demanded from the elite, but minimal performance is accepted from the majority of students. Some may believe that America can prosper with only the elite being well-educated, but the wasted human potential is unconscionable. Mediocre schooling affects the quality of our politics, culture, economy, and our communities (NCEE, 1998).

Contributions of the Present Study

1. Representativeness of the Sample. Demographics of the sample were compared to research done by Boylan (1999b), and Saxon and Boylan (1999).

2. Investigated Reliability and Validity. Reliability and pattern/structure coefficients were reported for the present study. Analyses for reliability were conducted on the variables for algebra concepts, mathematics anxiety, and mathematics attitude. Reliability refers to the reliability of the scores and not to the test. The same test administered to a new sample will have different reliability coefficients. Failure to report reliability coefficients may lead to misinterpretations and may result in studies that

cannot produce noteworthy effect sizes regardless of the sample size (Thompson, 2006). Furthermore, factor analysis was conducted to determine validity of the scores on the criterion measure (Pallant, 2001).

3. Multivariate Analysis. A particular strength of the present study is the use of Multivariate Analysis of Variance (MANOVA). Multivariate analysis simultaneously considers the relationships between variables and allows researchers to investigate relationships among two or more variables at one time versus investigating relationships one at a time (Garson, 2001; Pallant, 2001). This honors the reality of the data and controls the experiment wise alpha level.

4. Differences on Algebra Pretest to Posttest. Previous studies found no statistical significant differences in algebra pretests posttests between groups of students assigned to different treatments. The present study looked at other differences such as changes in mathematics anxiety and mathematics attitude.

Summary and Discussion

The purpose of this study was to investigate the effects of a web-based technology centric course, Assessment and Learning in Knowledge Spaces (ALEKS), on the remediation of college freshmen enrolled in an Intermediate Algebra class compared to college freshmen enrolled in an Intermediate Algebra class taught using a traditional lecture method. Mathematics anxiety and attitude toward mathematics were also investigated to determine if ALEKS could lower the anxiety associated with mathematics, as well as change attitudes.

The 48 items of the National Achievement Test, First Year Algebra Test

(NATFYAT) were subjected to a principal component analysis (PCA). The conclusion was that the 48 items tested for one factor: algebra concepts. Principal component analysis revealed the presence of two components shown in Table 10 for mathematics anxiety. An inspection of the scree plot presented in Figure 1 revealed a clear break after the second component. The pattern/structure coefficients of the rotated solution presented in Tables 9 and 10 reveal the presence of simple structure (Thurstone, 1935) for the mathematics anxiety. For mathematics attitude, principal component analysis revealed the presence of four components shown in Tables 11 and 12. An inspection of the scree plot shown in Figure 2 revealed a clear break after the fourth component. The rotated solution, as shown in Tables 13 and 14, revealed the presence of simple structure (Thurstone, 1935).

Research Question I

Does a mastery learning perspective of remediation, where students are expected to learn all the objectives in an Intermediate Algebra class, make a difference in mathematics achievement?

ALEKS is a computer algebra system based on a mastery learning perspective that is accessed from the Internet. The students are given an assessment at the beginning of the semester to determine placement. Each student begins working on the level of mathematical concepts that the assessment indicated the student is ready to learn. The students are expected to master 160 objectives in 15 weeks. ALEKS is a self-paced mathematics system that assesses students continuously with immediate positive feedback. Two universities participated in a research study that used ALEKS as the delivery of the instruction for the Intermediate Algebra students assigned to the classes. Students were assigned to this class because of scores made on the SAT.

The algebra test was given to the Experimental group (n = 54). The test is a National Achievement Test, First Year Algebra Test consisting of 48 questions that Intermediate Algebra students would encounter in an Intermediate Algebra course. The students were given the test in September and again in December. The intervention (ALEKS) began as soon as the pretest was completed. The students were given the posttest at the end of the semester.

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the algebra pretest and posttest given to the Experimental group only. As shown in the scatterplot in Figure 3, there was a positive correlation. The relationship between the algebra pretest and posttest was investigated using a Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables ($r = .411$, $n =54$, $p = .002$), with higher scores on the pretest associated with higher scores on the posttest, as can be seen in Table 15. Calculating the coefficient of determination resulted in explaining 17% of the variance.

Results from the paired-samples *t*-test indicated statistical significant differences on algebra achievement from the pretest ($M = 16.56$, S$D = 5.493$) to the posttest ($M = 20.56$, S$D = 5.67$). This is shown in Tables 15 and 16 ($t(53) = -4.490$, $p = .0001$). These results suggest that mathematical achievement did improve because of ALEKS.

Research Question I Answer

Does a mastery learning perspective of remediation, where students are expected to learn all the objectives in an Intermediate Algebra class, make a difference in mathematics achievement?

The data analysis suggested that mathematical achievement improves because of using the computer algebra system, ALEKS. The mean scores went from 16.56 to 20.56 an increase that is statistically significant, with a Cohen's *d* of about 0.611.

Research Question II

What differences exist between students using Assessments and Learning in Knowledge Spaces (ALEKS) compared to students who are taught Intermediate Algebra using a traditional lecture style?

Students enrolled in Intermediate Algebra classes were given the algebra, Mathematics Anxiety Rating Scale, and Mathematics Attitude tests. The two groups of students were either enrolled in a course that used computer generated instruction (n = 54) or lecture (n = 39). The scores on the three tests were analyzed to see if differences between the two groups existed. Results showed that the Control group outperformed the Experimental group on the algebra test, but the anxiety level of the Experimental group decreased and the attitude of the Experimental group increased. These findings are discussed in greater detail in the following sections.

Differences between Groups on the Algebra Test

The algebra test was administered to both the Experimental (n = 54) and Control (n = 39) groups. The test is a National Achievement Test, First Year Algebra Test (NATFYAT) consisting of 48 questions that Intermediate Algebra students would encounter in a college course. The students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest at the end of the semester.

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the algebra pretest and posttest given to the Experimental and Control groups. As shown in Figure 4, there appears to be a positive relationship between pretest and posttest scores. The relationship between algebra pretest and posttest was investigated using a Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables for Experimental (r = .411, n =54, p = .002) and a smaller correlation for the Control (r = .203, n = 39, p = .213), with higher scores on the pretest associated with higher scores on the posttest displayed in Table 17 explaining 17% and 4% of the variance respectively.

Results from paired-samples *t*-test indicated statistically significant differences on algebra achievement for the Experimental group from the pretest (M = 16.56, SD = 5.493) to the posttest (M = 20.56, SD = 6.674), and the Control group pretest (M = 13.89, SD = 5.493) to the posttest (M = 19.67, SD = 6.674), shown in Tables 17 and 18 (t (53) = -4.490, p = .0001). These results suggest that there are differences. On further examination of the means, the rate of change over time of the Control group was greater than the rate of change over time of the Experimental group, indicating that the Control group outperformed the Experimental group.

Differences on the Mathematics Anxiety Rating Scale

The Mathematics Anxiety Rating Scale test was administered to the Experimental group (n = 54) and the Control group (n =39). The Mathematics Anxiety

Rating Scale (MARS) consists of 30 questions on perceived anxiety of mathematics students. The minimum possible points on this test were 30, indicating no anxiety, and maximum possible points of 150, indicating extreme anxiety. After a factor analysis was conducted, the two components were labeled Perceived Mathematics Anxiety when considering taking a mathematics test and Calculating Mathematical Problems. The students were given the anxiety test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest near the end of the semester in December. Lower scores on the posttest MARS indicated less anxiety.

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the MARS pretest and posttest given to the Experimental group and the Control group. As shown in the scatterplot in Figures 7 through 9, there is a positive correlation. The relationship between the MARS pretest and posttest was investigated using a Pearson *r* correlation coefficient. There was a medium positive correlation between the two variables (r = .550, n =54, p = .0001), with higher scores on the pretest associated with higher scores on the posttest for the Experimental group explaining 30% of the variance. There was a medium positive correlation between the two variables (r = .627, n = 39, p = .0001), with higher scores on the pretest associated with higher scores on the posttest for the Control group, explaining 39% of the variance. There was also a medium positive correlation between both (Experimental and Control) groups between the two variables (r = .585, n = 93, p = .0001), with higher scores on the pretest associated with higher scores on the posttest, explaining 34% of the variance.

Results from paired-samples *t*-test show there was a statistically significant difference from pretest (M = 79.54, SD = 18.01) to posttest (M = 66.61, SD = 18.95), as shown in Tables 19 and 20 for the Experimental group ($t(53) = 5.41$, $p < .001$). There was not a statistically significant difference from pretest (M = 83.59, SD = 18.04) to posttest (M = 78.46, SD = 18.67), as shown in Tables 19 and 21 for the Control group ($t(38) = 2.02$, $p = .051$). There was a statistically significant difference from pretest (M = 81.24, SD = 18.070) to posttest (M = 71.58, SD = 19.632), as shown in Tables 19 and 22 for both (Experimental and Control) groups ($t(93) = 5.40$, $p < .001$). For the Experimental group the rate of change was (m = 12.93), for the Control group (m = 5.13), and for both groups (m = 9.65). Results suggest that the anxiety level of the Experimental group and the Control group both decreased, but the anxiety level of the Experimental group decreased substantially more than the Control group.

Differences on the Mathematics Attitude

The Fennama-Sherman Mathematics Attitude (MA) test was given to the Experimental group (n = 54) and the Control group (n =39). The MA test consists of 47 questions, divided into four categories: (a) Confidence toward mathematics (MAC), (b) Usefulness of mathematics (MAU), (c) Teacher influence (MAT), and (d) Male dominance (MAM). The four categories test for positive and negative attitudes. The Fennama-Sherman Mathematics Attitude scale is a Likert Scale testing for positive and negative attitudes. The positive questions are scored 5 to 1, and the negative questions are scored 1 to 5, with a possible score of 235 (all 47 questions), giving the highest possible score indicating high positive attitude toward mathematics down to 47 (all 47 questions), giving the lowest possible score indicating very poor attitude towards mathematics. The students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest near the end of the semester in December.

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the MA pretest and posttest given to the Experimental group and Control group. A positive correlation can be seen in the scatterplots shown in Figures 12 through 14. An analysis was conducted on the four components for further investigation reported in question five.

Results of paired-samples *t*-test shows there was not a statistically significant difference for the Experimental group from the pretest (M = 176.02, SD = 21.77) to the posttest (M = 179.61, SD = 22.61) as shown in Table 23 ($t(53) = -1.52$, $p = .136$). There was a statistically significant difference for the Control group from the pretest (M = 170.59, SD = 23.10) to posttest (M = 162.41, SD = 22.09) as shown in Table 23 ($t(38) = 2.15$, $p = .038$). There was not a statistically significant difference between both (Experimental and Control) groups from the pretest (M = 173.74, SD = 22.724) to the posttest (M = 172.40, SD = 23.852) as seen in Table 23 ($t(93) = .592$, $p = .540$). The results here suggest that statistical significance did not occur for the Experimental group but their attitudes toward mathematics did improve. On the other hand, the Control group showed statistical significance but their scores showed that their attitude toward mathematics was not as good at the end of the semester.

Research Question II Answer

Does a mastery learning perspective of remediation, where students are expected to learn all the objectives in an Intermediate Algebra class, make a difference in mathematics achievement?

Results from the analysis of the data suggest that both groups improved on the algebra tests, but the Control group outperformed the Experimental group. Mathematics anxiety decreased at a greater rate in the Experimental group than the Control group; therefore, the anxiety of the Experimental group was much less than the anxiety in the Control group. Even though the mathematics attitude in the Experimental group was not statistically significant, the attitudes of the Experimental group did improve. The Control group was statistically significant, but their attitudes toward mathematics did not improve. Their attitudes toward mathematics were worse at the end of the semester.

Research Question III

Are there differential mathematics effects for either group based on demographic factors such as gender, age, ethnicity, number of mathematics courses taken in the past, and degree plans?

Gender

A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the algebra pretest and posttest by gender. A positive correlation can be seen in the scatterplot in Figure 17. The relationship between algebra pretest and posttest was investigated using a Pearson *r* correlation coefficient. Results shows there was a medium positive correlation between the two variables for males (r = .510, n =37, p = .001), females (r = .626, n =56, p < .001), and both (r = .585, n =93, p < .001), with higher scores on the pretest associated with higher scores on the posttest with 26%, 39%, and 34% of the variance explained, respectively.

Age

A Pearson r correlation was conducted to test differences between age groups. In this study, 86% of the participants were 24 years or younger. Results show that there was a small correlation for eighteen year olds (n = 52, r = .379, p = .005), explaining 14% of the variance. There was also a small correlation for nineteen year olds (n = 11, r = -.204, p = .548), explaining 4% of the variance, and a large correlation for twenty year olds (n = 8, r = .867, p = .005), explaining 75% of the variance. There was a small correlation for twenty-one year olds (n = 5, r = .354, p = .559), explaining 12.5% of the variance, and a medium correlation for twenty-three year olds (n = 3, r=-.568, p= .615), explaining 32% of the variance. The other age groups had only one or two participants, as shown in Table 27.

Ethnicity

Results from an ANOVA on gain scores showed there was not a statistical significant difference by ethnicity. Table 28 shows the descriptive statistics for the group by ethnicity.

Research Question III Answer

Are there differential mathematics effects for either group based on demographic factors such as gender, age, ethnicity, number of mathematics courses taken in the past, and degree plans?

Results showed that there were no differences in mathematical achievement by gender, ethnicity, or age. Students enrolling in college have come from secondary schools that require at least 3 years of mathematics in high school so there was no variance for this factor. All students reported that they planned to complete either a two or a four-year program, so there was no variance for this factor.

Research Question IV

Do differences emerge between the two groups of students in their perceived level of mathematics anxiety?

The Mathematics Anxiety Rating Scale (MARS) test was given to the Experimental group (n = 54) and the Control group (n =39). The MARS consists of 30 questions relating the perceived anxiety of mathematics students when considering taking a mathematics test and calculating mathematical problems. The students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest near the end of the semester.

A Pearson r correlation analysis was conducted to describe the strength and direction of the linear relationship between the pretest and posttest MARS given to the Experimental group and Control group. A scatterplot was first examined to view the relationship between the pretest and posttest MARS, as seen in Figures 20 to 22. A positive correlation can be seen in the scatterplot.

Descriptive statistics are shown in Tables 31 through 33, with higher scores on the pretest associated with higher scores on the posttest for the Experimental, Control, and both groups. Results from conducting a Pearson *r* correlation coefficient showed a medium positive correlation between the two variables (r = .550, n =54, p < .001) for the Experimental group. There was a medium positive correlation between the two variables (r = .627, n = 39, p < .001) for the Control group. There was also a medium positive correlation between the two groups (Experimental and Control) between the two variables (r = .585, n = 93, p < .001).

Results from paired-samples *t*-test show there was a statistically significant difference for the Experimental group from pretest (M = 79.54, SD = 18.01) to posttest (M = 66.61, SD = 18.59), (t(53) = 5.405, p < .001). Results show there was no statistically significant difference for the Control group from pretest (M = 83.59, SD = 18.042) to posttest (M = 78.46, p = 18.67), (t(38) = 2.018, p = .051). There was a statistically significant difference for both (Experimental and Control) groups from pretest (M = 81.24, SD = 18.07) to posttest (M = 71.58, SD = 19.63), (t(93) = 5.404, p < .001). Cohen's d = .736 (Experimental group), Cohen's d = .424 (Control group), and Cohen's d = .560 (for both groups).

The results from a MANOVA showed statistically significant differences did exist between the Experimental and Control groups of students on MARS pretest and posttest (F(2, 90) = 4.773, p = .011) with moderate effect size of (η^2 = .10).

Research Question IV Answer

Do differences emerge between the two groups of students in their perceived level of mathematics anxiety?

Results from the analysis of the data show that the anxiety of the Experimental and Control groups decreased from the beginning of the semester to the end of the semester. The Experimental group's mathematics anxiety decreased at a greater rate than the Control group. Even though the anxiety level of both groups decreased over time, the students in ALEKS seemed to be less anxious.

Research Question V

Is the student's attitude toward mathematics a factor in student's inability to be successful in Intermediate Algebra?

The Fennema-Sherman Mathematics Attitude (MA) test was administered to the Experimental group (n = 54) and the Control group (n =39). The MA consists of 47 questions divided into four categories: (a) Confidence toward mathematics (MAC), (b) Usefulness of mathematics (MAU), (c) Teacher influence (MAT), and (d) Male dominance (MAM). The four categories test for positive and negative attitudes. The Fennama-Sherman Mathematics Attitude scale is a Likert Scale testing for positive and negative attitudes. The positive questions are scored 5 to 1, and the negative questions are scored 1 to 5 with a possible score of 235 (all 47 questions) giving the most positive attitude results down to 47 (all 47 questions), indicating a very poor attitude towards mathematics. The students were given the test in September and again in December. The intervention began as soon as the pretest was completed. The students were given the posttest near the end of the semester in December.

A Pearson r correlation analysis was conducted to describe the strength and direction of the linear relationship between the MA pretest and posttest given to the Experimental group and Control group. There is a positive correlation between pretest and posttest scores, as can be seen in the scatterplots in Figures 24 and 25.

Results from conducting a Pearson *r* correlation coefficient showed a medium positive correlation between the two variables comparing the Experimental group only ($r = .693$, $n = 54$, $p < .001$), with higher scores on the pretest associated with higher scores on the posttest for the Experimental group. There was a medium positive correlation between the two variables comparing the Control group only ($r = .466$, $n = 39$, $p = .003$), with higher scores on the pretest associated with higher scores on the posttest for the Control group. There was a medium positive correlation between both groups (Experimental and Control) and between the two variables ($r = .592$, $n = 93$, $p < .001$), with higher scores on the pretest associated with higher scores on the posttest. Results from a paired-samples *t*-test showed there was not a statistically significant difference for the Experimental group from pretest ($M = 176.02$, $SD = 21.770$) to posttest ($M = 178.61$, $SD = 22.61$), as seen in Tables 34 and 37 ($t(53) = -1.516$, $p = .136$). There was a statistically significant difference for the Control group from pretest ($M = 170.59$, $SD = 23.10$) to posttest ($M = 162.41$, $SD = 22.09$), as seen in Tables 35 and 37 ($t(38) = 2.145$, $p = .038$). There was not a statistically significant difference in both (Experimental and Control) groups from pretest ($M = 173.74$, $SD = 22.72$) to posttest ($M = 172.40$, $SD = 23.85$), as seen in Tables 36 and 37 ($t(93) = .592$, $p = .540$).

The results of a MANOVA showed statistically significant differences did exist between Experimental and Control groups of students on MA pretest and posttest ($F(2,90) = 7.41$, $p = .001$) with a moderate effect size of ($\eta^2 = .14$). A Pearson *r* correlation analysis was conducted to describe the strength and direction of the linear relationship between the MA pretest and posttest given to the Experimental group and Control group. Scatterplots suggest positive correlations between the MA pretest and posttest for the four categories, as seen in Figures 26 through 40. Results from a Pearson *r* correlation coefficient suggest there was a medium positive correlation between the two variables (r = .693, n =54, p < .001), with higher scores on the pretest associated with higher scores on the posttest for the Experimental group. There was a medium positive correlation between the two variables (r = .466, n = 39, p < .001), with higher scores on the pretest associated with higher scores on the posttest for the Control group. There was a medium positive correlation between both groups (Experimental and Control) between the two variables (r = .592, n = 93, p < .001), with higher scores on the pretest associated with higher scores on the posttest.

Results from a paired-samples *t*-test on the four components of the MA (MAC, MAT, MAU, and MAM) showed there was not a statistically significant difference for the Experimental group from pretest (M = 176.02, S*D* = 21.77) to posttest (M = 179.61, S*D* = 22.61), as seen in Tables 34 and 37 ($t(53)$ = -1.516, p = .136). There was a statistically significant difference for the Control group from pretest (M = 170.59, S*D* = 23.91) to posttest (M = 162.41, S*D* = 22.09), as seen in Tables 35 and 37 ($t(38)$ = 2.145, p = .038). There was not a statistically significant difference for both (Experimental and Control) groups from pretest (M = 173.74, S*D* = 22.72) to posttest (M = 172.40, S*D* = 23.852), as seen in Tables 36 and 37 ($t(93)$ = .592, p = .540). The rate of change for the Experimental group on MAC increased at a greater rate than the Control group, although the Control group also increased very slightly. The rate of change for the Experimental group on MAT increased, while the Control group decreased. The rate of change for the Experimental group on MAU slightly decreased, while the Control group decreased at a greater rate. The rate of change for the Experimental group on MAM decreased, while the Control group decreased at a similar rate. The Experimental group results suggested that there was no statistically significant difference, but their attitudes toward mathematics did improve. Results suggested that, even though a statistical significance was found for the Control group, their attitudes toward mathematics were not as good as their attitudes were at the beginning of the semester.

The results of a MANOVA of the four components: Confidence, Usefulness, Teacher, and Male Dominance showed statistically significant differences did exist between Experimental and Control groups of students on MA pretest and posttest for the four components ($F(8,84) = 2.646891$, $p = .012$) with moderate effect size of (η^2 = .201).

Research Question V Answer

Do attitudes toward mathematics contribute to a student's inability to be successful in a mathematics course?

The results show that the Experimental group's attitudes did increase, but did not show statistically significance, and their mathematics achievement did improve. In conclusion, mathematics attitude possibly could contribute to mathematical achievement. On the other hand, the Control group's attitudes did show statistical significance, but that significance was negative, not positive, and their attitudes toward mathematics were not as good by the end of the semester, even though their performance on the algebra test increased at a greater rate than did the Experimental group. In this case, the conclusion has to be that mathematics attitude did not positively contribute to their mathematics achievement.

Research Question VI

Is there differential performance between students who use ALEKS and Control group counterparts, and are there measurable differences one, two, and three years after completing the program?

The algebra, Mathematics Anxiety Rating Scale, and Mathematics Attitude test was given to the Experimental group (n = 29) and the Control group (n =39). The results of the MANOVA showed statistically significant differences did not exist between Experimental and Control groups of students on the three tests ($F(3, 64) = 1.89062$, p = .140), with a moderate effect size of ($\eta^2 = .08$).

The results of the interviews with past Experimental students (n = 10) showed that overall the students preferred ALEKS to lectures. During the interview, I asked the students at LeTourneau University what they liked about ALEKS. The students said they liked the fact that ALEKS was self-paced with immediate feedback so they knew if what they did was correct or incorrect. They also said great instructions were available, there was easy accessibility, and they did not have to be in the lab at school to work on ALEKS. The negative comments about ALEKS were the students did not like the fact that some of the questions asked were concepts that they had not yet reviewed, and the tests could take away objectives already done.

Current students, as well as students from the past, have also asked to drop

Intermediate Algebra using ALEKS if they knew they were not going to be able to finish all of the objectives required. Students indicated they would be enrolling in another ALEKS Intermediate Algebra class because they believed they would fail if enrolled in a lecture class. The students then enrolled in the ALEKS Intermediate Algebra class the following semester. Some students asked if they could also take the College Algebra courses using ALEKS even though all the College Algebra courses offered are only lecture courses. The head of the Mathematics Department approves of this and allows the students to use ALEKS instead of the lecture classes for College Algebra. Because interviews were not conducted with the Control group, information about student drop-rates was not available for the non-ALEKS group.

Research Question VI Answer

Is there differential performance between students who use ALEKS and Control group counterparts, and are there differences measurable one, two, and three years after completing the program?

The results showed that there was not statistically significant differences between these two groups of students. The interviews with the Experimental group revealed that they preferred ALEKS. ALEKS was much more interactive than being in a lecture type class and they were allowed to work at their own pace.

Summary of Important Results

With the large number of students enrolling in post-secondary school underprepared, it is important to continue to investigate the best practices for teaching these students. The present study investigated an intervention using a computer algebra system (ALEKS) accessed from the internet to see if there were differences between students enrolled in an ALEKS Intermediate Algebra course and students taught by a traditional lecture method.

The students participating in this research (*n*=93) were enrolled in and Intermediate Algebra course because of their scores on the SAT or the THEA. These students were attending universities and community colleges in Texas. The Experimental group (*n*=54) and the Control group (*n*=39) were given pretests and posttests for algebra, mathematics anxiety, and mathematics attitude. The coefficient alpha score reliability for the algebra pretest was .701, algebra posttest was .793, MARS pretest was .905, MARS posttest was .930, MA pretest was .926, and MA posttest was .929.

The demographics of the participants in this study were very close to the national averages. The percentages of females that are in developmental classes nationally are 55% compared to 60% in this study. The percentages of males that are in developmental classes nationally are 45% compared to 40% in this study. The national average age in developmental education classes is 23 compared to 21 in this study. Students under 24 nationally make up 59% compared to 86% in this study. Students between 25 and 34 make up 24% compared to 6% in this study, and students over 35 make up 17% nationally compared to 8% in this study. Ethnicities nationally are Caucasian 59%, African American 23%, Hispanic 6%, Asian 3%, and American Indian 1%, compared to Caucasian 69%, African American10%, Hispanic 16%, and Other 5% in this study.

Underprepared students will enroll in colleges and universities, and these students will need assistance (Casazza, 1999). The open door policy has encouraged many more students to pursue a college education, even though the student may not be academically prepared. These students believe the only way to a better life is through a college education. The colleges and universities must rely on research for best practices for teaching this growing population of students to ensure they receive the education they seek and deserve. The present study investigated developmental students enrolled in an Intermediate Algebra class for mathematics achievement, anxiety associated with mathematics, and attitudes toward mathematics with three take-home messages for developmental teachers.

Methods of Instruction for Developmental Students

Teachers of developmental students must investigate and implement the best practices for their underprepared students. Boylan (2002) has done extensive research in this area so the information is readily available. The results of this study suggest that a computer-mediated curriculum does improve mathematical achievement for some students. For other students, the lecture method seems to be best. Teachers must evaluate what is best for their students and implement these best practices.

Mathematics Anxiety

Teachers must be aware that developmental students have had many years of frustration and anxiety associated with mathematics. Teachers must find ways to alleviate this anxiety so that the students become confident in their ability to learn mathematics. The present study suggests that the students’ anxiety level was decreased after a semester of using the computer-mediated algebra instruction.

Mathematics Attitude

Teachers of developmental students must understand that negative attitudes toward mathematics can affect the ability of their students to learn mathematics. Teachers can play an important role in the lives of their students by helping students see the usefulness of mathematics. Teachers can also encourage students in such a way that they become confident in the teacher, in themselves, and in their ability to learn mathematics. The present study suggests that the students' attitude toward mathematics was greatly increased after a semester of using the computer-mediated instruction.

Future Research

With the large number of underprepared students enrolling and attending colleges and universities in the United States, research must continue to ensure that these students will receive the help that they so desperately need. Research shows that only 20% of developmental students enrolling in college and universities will actually earn a degree, compared to 50% of regular students (Maxwell, 1979). Evidently research has not found the answer to retaining and educating developmental students, or maybe research has found solutions, but researchers have not found a way to implement these findings to bring about lasting change. The findings in the present research indicate that there are anxiety issues, as well as negative attitudes, that can affect mathematical achievement, and that a computer algebra program can be just as affective as lecture classes in teaching mathematics.

The present study suggests that underprepared students can learn from different means (i.e., computer algebra or lecture), and research needs to continue to investigate the best practices for these students. Researchers need to be diligent about finding what method will help these students. Further research should be conducted on this growing population of college and universities.

Further research should also be done on the affects of anxiety and attitudes toward mathematics. That anxiety affects mathematical learning has been known for over 30 years, and further research needs to be done on best practices for alleviating the stress associated with mathematics. Research has also been done for over 30 years on attitudes toward mathematics and this research indicates that attitudes do affect mathematical learning. Further research needs to be done to find out how instructors can help change the negative attitudes associated with mathematics.

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APPENDIX A

Institution	Entrance Exam Given
College 1	THEA
College 2	THEA
College 3	THEA
University 1	SAT
University 2	SAT

APPENDIX B

--- DIRECTIONS ---

Do not turn this page until you are told to do so.

This is a test of your knowledge of first year algebra. For each question, there are five possible answers, only one of which is correct. Read each exercise carefully and do exactly what it tells you to do. By working each problem, find which answer is correct; then draw a line under the letter that corresponds to the correct answer in the answer column. As you work through the problems, you should omit those that seem unusually difficult until you have finished the others. Then come back to those you have omitted if you have time. When you are asked to stop, do so immediately.

There are 48 exercises in this test.

The working time for the test is 40 minutes.

--- EXAMPLES ---

The sum of 3x and 5x is

A. 2x D. $\frac{3}{5}x$

B. 8x E. none of these

C. 15x

Because the correct answer is B, a line is drawn under B

If 4x=12, then x equals

A. 8 D. $9\frac{1}{3}$

B. 16 E. none of these

C. 48

Add $-3x^2$ and $5x^2$. The sum is

A. $2x^2$ D. $-2x^2$

B. $2x^4$ E. none of these

C. $-15x^2$

Subtract -3m from 2m. The difference is

A. –m
B. 5m
C. -5m
D. $-6m^2$
E. none of these

The expression 3x-2-2 (3x-7), when simplified, equals

A. 3x-12
B. 9x+14
C. 3x+12
D. D. 0
E. -3x+12

Simplify the expression: $2(3x-x^2) – 2x(3+x)$. The result is

A. $15x^5$
B. 0
C. $-4x^2$
D. $4x^2$
E. none of these

Multiply $3x^2$ by $-5x^3$. The product is

A. $-15x^6$
B. -15x
C. $15x^5$
D. $15x^6$
E. none of these

Multiply (3a +5) (a-1). The product is

A. $3a^2-5$
B. $3a^2 + 2a-5$
C. $3a^2 + 5$
D. $3a^2 + 2a + 5$
E. none of these

Divide -4xy by 4x. The quotient is

A. y
B. -1
C. –y
D. xy
E. none of these

Divide $18x^3$-24xy by (-6x). The quotient is

A. $3x^2+4y$
B. $-3x^2+4y$
C. $-3x^2-4y$
D. $3x^2-4y$
E. none of these

Equations such as d = rt, A= $\frac{1}{2}$ bh and C = πD are called?
A. Binomials D. Formulas
B. Polynomials E. none of these
C. Literal expressions

If 9-a = 0.5a, then a equals
A. 0.4 D. 9.5
B. 6.0 E. 4a
C. 8.5

Find the value of x if 2x-5 = 7x-15.
A. 0 D. 2
B. -2 E. 3
C. 4

If $\frac{20+a}{a^2}$ = M, find the value of M when a = 5.
A. $\frac{3}{5}$ D. 1
B. 5 E. 0
C. 4

In the equation x + 6 = 13, the answer 7 is called
A. A factor D. A power
B. A coefficient E. none of these
C. A root

Given the formula: K = a (b-12). If K = 144 and a = 12. What number does b equal?
A. 0 D. 14
B. 13 E. 24
C. 12

A square root of 81 a^{36} is
A. $9a^{18}$ D. $9a^{34}$
B. $9a^{6}$ E. none of these
C. $9a^{9}$

Rationalize the denominator $\frac{3}{\sqrt{3}}$. The result is

A. $\sqrt{3}$

B. $\frac{\sqrt{3}}{3}$

C. 3

D. $3\sqrt{3}$

E. $\frac{1}{3}$

Rationalize the denominator $\frac{\sqrt{15}}{\sqrt{3}}$. The result is

A. $\frac{\sqrt{5}}{3}$

B. $3\sqrt{5}$

C. $\sqrt{5}$

D. $5\sqrt{3}$

E. 5

Express in simplest form $3\sqrt{2}$ -2$\sqrt{50}$. The result is

A. 60

B. -7$\sqrt{2}$

C. -13$\sqrt{2}$

D. -7

E. 7$\sqrt{2}$

What are the factors of $25x^2 – 70x + 49$?

A. (5x+7)(5x-7)

B. (5x+49)(5x-1)

C. (5x-7)

D. $(5x+7)^2$

E. $(5x-7)^2$

Reduce to lowest terms: $\frac{3m-3n}{m^2-n^2}$. The result is

A. $\frac{3}{mn}$

B. $\frac{3}{m-n}$

C. $\frac{3}{m+n}$

D. m + n

E. m – n

Reduce to lowest terms: $\frac{2r^2 - 2r - 24}{3r^2 - 3r - 36}$. The result is

A. $\frac{2r+6}{3r+9}$

B. $\frac{r+2}{r-3}$

C. 1

D. -$\frac{2}{3}$

E.

Change to a single fraction: $\frac{5}{3x+3y}$ - $\frac{2}{2x+2y}$. The result is

A. $\frac{2}{x+y}$

B. $\frac{1}{6(x+y)}$

C. $\frac{2}{3(x+y)}$

D. $\frac{2}{5x+5y}$

E. none of these

Find the product of: $\frac{x+3}{x^2-4} \cdot \frac{2x+4}{3x+9}$. The result is

A. $\frac{2}{x-2}$

B. $\frac{x}{3}$

C. $\frac{2}{3x+3}$

D. $\frac{2}{5x+5y}$

E. $\frac{2}{9}$ x

Divide $\frac{a^2 - 2a}{a^2 - 4a + 4}$ by $\frac{a}{a-2}$. The result is

A. 0

B. a-2

C. a

D. $\frac{1}{a}$

E. 1

Solve for x: $\frac{x+5}{3} = \frac{x-10}{4}$. X equals

A. -50 D. -10

B. 50 E. $\frac{2}{3}$

C. 5

Solve for x: ax = bx + 3. x equals

A. 3ab D. $\frac{a+b}{3}$

B. a – b +3 E. $\frac{b+3}{a}$

C. $\frac{3}{a-b}$

Find two values of x if: $x^2 - 2x - 24 = 0$.

A. 6 and -4 D. (x-4) and (x+6)

B. 24 and -22 E. 2 and -6

C. -6 and 4

What is the remainder of $x^3 + 3x^2 - x - 2$ if divided by (x+2)?

A. 4 D. 8

B. -8 E. $\frac{-4}{x+2}$

C. -4

If a=2, b=3, x=4 and y=0, find the value of the expression $a^2x + bxy - 2ab - 3xy$. The result is

A. 40 D. 18

B. 38 E. 4

C. 28

Of x=mn+3p, find the value of x when m=2, n=3 and p=5. The result is

A. 58 D. 25

B. 45 E.

C. 28 21

Reduce to lowest terms: $\frac{a^2b - ab}{a^2b + ab}$. The result is

A. 1 D. $\frac{a-1}{a+1}$
B. -1 E. none of these
C. ab

Solve the following equations for x: $\left\{\begin{matrix} 3x = y \\ x - 2y = 15 \end{matrix}\right\}$

A. -3 D. -5
B. 3 E. 15
C. 5

Solve the following equations for y: $\left\{\begin{matrix} 3x + 2y = 7 \\ 4x + 3y = 10 \end{matrix}\right\}$

A. 1 D. -2
B. -1 E. 3
C. 2

If K = $\frac{mn}{2}$, the n equals

A. $\frac{Kn}{2}$ D. $\frac{2K}{n}$
B. $\frac{K+n}{2}$ E. $\frac{2n}{K}$
C. 2Kn

Which of the following equations could be used to solve this problem:

The length of a rectangle is 8 inches more than the width of W. If the perimeter of the rectangle is 84 inches, what are its dimensions?
A. 2W + 8 = 84 D. 2W (W+8)= 84
B. 4W + 8 = 84 E. none of these
C. 4W + 16 = 84

In one city, the cost of telephone calls is 8 cents each for the first 50 calls and 5 cents for each additional call during the month. If one family makes 50 + E calls in a month, what is the total cost in dollars?

A. 4 + 0.05E
B. 4+ 0.05(50 + E)
C. 0.08 (50+E)
D. 4+ 0.01 E
E. none of these

If xy = 40 and x decreases in value but remains positive, then y

A. decreases in value
B. increases in value
C. remains the same value
D. doubles in value
E. none of these

Given: $y = 2 + \frac{1}{1-x}$. If x increases from 2 to 5, then y

A. increases in value
B. decreases in value
C. remains the same value
D. doubles in value
E. none of these

If the graph of the equation y = 3x+b passes through the point (3,2), then b equals what number?

A. 1
B. -1
C. -4
D. -7
E. none of these

The graph of the equation 5x + my = -7 passes through the point (4,-3). What is the value of m?

A. 1
B. -3
C. 4
D. 9
E. none of these

The graph of the equation $y = x^2 - 49$ crosses the positive x-axis at what point?

A. (0, -7)
B. (7, 0)
C. (7, -7)
D. (7, 7)
E. none of these

What number must be added to both terms of the fraction $\frac{5}{13}$ to obtain a fraction whose value is $\frac{3}{5}$?

A. 2 D. 7
B. 5 E. 12
C. 8

The product of the sum and difference of two numbers, m and n, is equal in terms of m and n to what expression?

A. m+n D. $(m-n)^2$
B. m^2n^2 E. m^2-n^2
C. $(m+n)^2$

One pipe can fill a tank in 3 hours; a second pipe can fill the same tank in 6 hours. How long will it take to fill the tank if both pipes are used at the same time?

A. $1\frac{1}{2}$ hours D. $4\frac{1}{2}$ hours
B. 2 hours E. none of these
C. 3 hours

If x objects cost c cents, how many objects of the same kind can be bought for 2c cents?

A. 2 D. $\frac{2c}{x}$
B. 2x E. 2c
C. 2cx

A cargo plane, flying 300 miles per hour, left an airport. A jet plane took off 3 hours later and flew in the same direction as the cargo plane. The jet flew at an average speed of 750 miles per hour. How long after the take-off did the jet overtake the cargo plane?

A. 2 hours D. $4\frac{1}{2}$ hours
B. $2\frac{1}{2}$ hours E. 5 hours
C. 3 hours

A man had $2800 invested, part at 5% and the remainder at 6%. If his yearly income from both investments is $152, find the number of dollars invested at 6%?

A. $68 D. $1400
B. $200 E. $1800
C. $1200

A news boy sold the Daily Star for 15¢ each and the Daily Citizen for 7¢ each. He sold 85 papers in all and received $9.07. How many Stars did he sell?

A. 39 D. 23
B. 37 E. 46
C. 31

Mathematics Anxiety Rating Scale: Short Version

The items in the questionnaire refer to things that may cause fear or apprehension. For each item, place a check in the box under the column that describes how much you are frightened by it nowadays. Work quickly but be sure to consider each item individually.

	Not At All	A little	A Fair Amount	Much	Very Much
Taking an examination (final) in a math course.	☐	☐	☐	☐	☐
Thinking about an upcoming math test one week before.	☐	☐	☐	☐	☐
Thinking about an upcoming math test one day before.	☐	☐	☐	☐	☐
Thinking about an upcoming math test one hour before.	☐	☐	☐	☐	☐
Thinking about an upcoming math test five minutes before.	☐	☐	☐	☐	☐
Waiting to get a math test returned in which you expected to do well.	☐	☐	☐	☐	☐

	Not At All	A little	A Fair Amount	Much	Very Much
Receiving your final math grade in the mail.	□	□	□	□	□
Realizing that you have to take a certain number of math classes to fulfill the requirements in your major.	□	□	□	□	□
Being given a “pop” quiz in a math class.	□	□	□	□	□
Studying for a math test.	□	□	□	□	□
Taking the math section of a college entrance exam.	□	□	□	□	□
Taking an examination (quiz) in a math course.	□	□	□	□	□
Picking up the math textbook to begin working on a homework assignment.	□	□	□	□	□
Being given a homework assignment of many difficult problems which is due the next class meeting.	□	□	□	□	□
Getting ready to study for a math test.	□	□	□	□	□
Dividing a five digit number by a two digit number in private with pencil and paper.	□	□	□	□	□
Adding up 976 + 777 on paper.	□	□	□	□	□
Reading a cash register receipt after your purchase.	□	□	□	□	□

	Not At All	A little	A Fair Amount	Much	Very Much
Figuring the sales tax on a purchase that costs more than $1.00.	☐	☐	☐	☐	☐
Figuring out your monthly budget.	☐	☐	☐	☐	☐
Being given a set of numerical problems involving addition to solve on paper.	☐	☐	☐	☐	☐
Having someone watch you as you total up a column of figures.	☐	☐	☐	☐	☐
Totaling up a dinner bill that you think overcharged you.	☐	☐	☐	☐	☐
Being responsible for collecting dues for an organization and keeping track of the amount.	☐	☐	☐	☐	☐
Studying for a driver's license test and memorizing the figures involved, such as the distances it takes to stop a car going at different speeds.	☐	☐	☐	☐	☐
Totaling up the dues received and the expenses of a club you belong to.	☐	☐	☐	☐	☐
Watching someone work with a calculator.	☐	☐	☐	☐	☐
Being given a set of division problems to solve.	☐	☐	☐	☐	☐
Being given a set of subtraction problems to solve.	☐	☐	☐	☐	☐
Being given a set of multiplication problems to solve.	☐	☐	☐	☐	☐

Instructions

Fennema-Sherman Mathematics Attitude Scale

Using this scale will help you and I find out how you feel about yourself and mathematics.

On the following pages is a series of sentences. You are to mark your answer sheets by telling how you feel about them. Suppose a statement says:

Example 1: I like mathematics.

As you read the sentence, you will know whether you agree or disagree. If you strongly agree, circle A next to Number 1. If you agree, but not so strongly, or you only “sort of” agree, circle B. If you disagree with the sentence very much, circle E for strongly disagree. If you disagree, but not so strongly, circle D. If you are not sure about a question or you can’t answer it, circle C. Now, mark you sheet, then go on and do Example 2.

Do not spend much time with any statement, but be sure to answer every statement.

Work fast, but carefully.

There are no “right” or “wrong” answers. The only correct responses are those that are true for you. Whenever possible, let the things that have happened to you help you make a choice.

A Modified Fennema-Sherman Mathematics Attitude Scale

	Strongly Agree	Agree	Not Sure	Disagree	Strongly Disagree
I am sure that I can learn math.	A	B	C	D	E
My teachers have been interested in my progress in math.	A	B	C	D	E
Knowing math will help me earn a living.	A	B	C	D	E
I don’t think I could do advanced math.	A	B	C	D	E
Math will not be important to me in my life’s work.	A	B	C	D	E

	Strongly Agree	Agree	Not Sure	Disagree	Strongly Disagree
Males are not naturally better than females in math.	A	B	C	D	E
Getting a teacher to take me seriously in math is a problem	A	B	C	D	E
Math is hard for me.	A	B	C	D	E
It’s hard to believe a female could be a genius in math.	A	B	C	D	E
I’ll need math for my future work.	A	B	C	D	E
When a woman has to solve a math problem, she should ask a man for help.	A	B	C	D	E
I am sure of myself when I do math.	A	B	C	D	E
I don’t expect to use much math when I get out of school.	A	B	C	D	E
I would talk to my math teachers about a career that uses math.	A	B	C	D	E
Women can do just as well as men in math.	A	B	C	D	E
It’s hared to get math teachers to respect me.	A	B	C	D	E
Math is a worthwhile, necessary subject.	A	B	C	D	E
I would have more faith in the answer for a math problem solved by a man than a woman.	A	B	C	D	E
I’m not the type to do well in math.	A	B	C	D	E
My teachers have encouraged me to study more math.	A	B	C	D	E
Taking math is a waste of time.	A	B	C	D	E

	Strongly Agree	Agree	Not Sure	Disagree	Strongly Disagree
I have a hard time getting teachers to talk seriously with me about math.	A	B	C	D	E
Math has been my worse subject.	A	B	C	D	E
Women who enjoy studying math are a little strange.	A	B	C	D	E
I think I could handle more difficult math.	A	B	C	D	E
My teachers think advanced math will be a waste of time for me.	A	B	C	D	E
I will use math in many ways as an adult.	A	B	C	D	E
Females are as good as males in geometry.	A	B	C	D	E
I see math as something I won't use very often when I get out of high school.	A	B	C	D	E
I feel that math teachers ignore me when I try to talk about something serious.	A	B	C	D	E
Women certainly are smart enough to do well in math.	A	B	C	D	E
Most subjects I can handle OK, but I just can't do a good job with math.	A	B	C	D	E
I can get good grades in math.	A	B	C	D	E
I'll need a good understanding of math for my future work.	A	B	C	D	E
My teachers want me to take all the math I can.	A	B	C	D	E
I would expect a woman mathematician to be a forceful type of person.	A	B	C	D	E
I know I can do well in math.	A	B	C	D	E

	Strongly Agree	Agree	Not Sure	Disagree	Strongly Disagree
Studying math is just as good for women as for men.	A	B	C	D	E
Doing well in math is not important for my future.	A	B	C	D	E
My teachers would not take me seriously if I told them I was interested in a career in science and math.	A	B	C	D	E
I am sure I could do advanced work in math.	A	B	C	D	E
Math is not important in my life.	A	B	C	D	E
I’m no good in math.	A	B	C	D	E
I study math because I know how useful it is.	A	B	C	D	E
Math teachers have made me feel I have the ability to go on in math.	A	B	C	D	E
I would trust a female just as much as I would trust a male to solve important math problems.	A	B	C	D	E
My teachers think I’m the kind of person who could do well in math.	A	B	C	D	E

APPENDIX C

Student Flyer

I really need your help. I am a researcher interested in mathematics education, and you could help me out by participating in my study. You will receive a coupon for free pizza, and you can choose to place your name in a drawing for other prizes which include an iPod or $50 gift certificates to Wal-Mart.

Instructions:
Open a web browser (such as Internet Explorer)
Go to http://online.letu.edu
Click the login button
Enter your username
Your user name is JTCC1
Your password is research
Click Login button
Click "Judy Taylor Mathematics Research" to enter the course site where the surveys are located.
Follow the instructions on the screen.

Student Flyer

I really need your help. I am a researcher interested in mathematics education, and you could help me out by participating in my study. You will receive a coupon for free pizza, and you can choose to place your name in a drawing for other prizes which include an iPod or $50 gift certificates to Wal-Mart.

Instructions:
Open a web browser (such as Internet Explorer)
Go to http://online.letu.edu
Click the login button
Enter your username
Your user name is JTCC2
Your password is research
Click Login button
Click "Judy Taylor Mathematics Research" to enter the course site where the surveys are located.
Follow the instructions on the screen.
Thank you for completing the pre-test!

I need your help again…
Please follow the steps below to complete the post-testing.
Upon completion of the study, your name will be entered in a drawing to win an Apple 512MB iPod shuffle or one of three $50 Wal-Mart gift certificates!

To participate in the study just follow the instructions below:

Open a web browser (such as Internet Explorer)
Go to http://online.letu.edu
Click the login button
Enter your username
Your user name is: JTBBRE
Your password is: research
Click Login button
Click “Judy Taylor Mathematics Research” to enter the course site where the surveys are located.
Follow the instructions on the screen.

Thanks so much for your participation!

APPENDIX D

Interview questions for students who took Intermediate Algebra using ALEKS one, two, and three years ago.

1. Describe your past experiences in mathematics classes prior coming to LeTourneau University. In what types of classes or through what kind of instruction have you learned the most mathematics?

2. What are your general thoughts on ALEKS?

   What did you like about ALEKS?

3. What did you dislike about ALEKS?

4. What would you suggest to improve ALEKS?

5. Do you think ALEKS prepared you for subsequent mathematics classes?

6. Do you have any other experiences with on-line learning? How would you compare ALEKS with your other on-line teaching/learning experiences?

APPENDIX E

From:	Richard Suinn [suinn@lamar.colostate.edu]	Sent:	Tue 7/4/2006 8:40 PM
To:	Taylor, Judy		
Cc:			
Subject:	re: MARS		
Attachments:			

This email is to give you permission to use the MARS for your dissertation research.

Richard M. Suinn, Ph.D.

VITA

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SELECTED PAPER SUBMITTED FOR PUBLICATION

Taylor, J. M., & Lee, J. (2006). Effective Mathematics Teaching: A Case Study of One Middle School Teacher. Paper submitted for publication to the *Journal of Mathematics Education.*

SELECTED PRESENTATION

Taylor, J. M., Capraro, R. M., & Capraro, M. M. (2004, April), Representational Models for the Teaching and Learning of Mathematics. Presented at the National Council for the Teaching of Mathematics national convention held in Philadelphia, PA.

New Artificial Intelligence Systems for Improving Student Math Skills: Assessment and LEarning in Knowledge Spaces (ALEKS)[1]

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***Abstract*—**

Artificial intelligence technology for advancing mathematical understanding is achieving new gains through a computer software called Assessment and Learning in Knowledge Spaces (ALEKS). ALEKS, an artificial intelligence system developed by a team of researchers at New York University and the University of California through the support of the National Science Foundation, is intended to form a basic framework of understanding for mathematics concepts. A growing number of high schools and institutions of higher learning have implemented ALEKS successfully into their classrooms. Over 120 ALEKS implementation sites around the country have been documented [1]. This paper will describe the application of ALEKS as part of a summer bridge program, called the Engineering Math Advancement Program (E-MAP), for building student skills at The University of Alabama's College of Engineering .

ALEKS keeps server statistics that measure the learning success of all students, namely how often they succeed at learning a topic that ALEKS offers them as "ready to learn." When ALEKS determines that a student is ready to learn a topic, the student is able to learn it a very high percentage of the time. In the small percentage of cases where the student is initially unsuccessful, the topic is presented again to the student later on. Because of the artificial intelligence in ALEKS, students are almost always successful at learning the material ALEKS offers them. The level of instructior involvement does not generally play a significant role. The average historical learning rates with ALEKS are ~90%.

Over the past four years, the University of Alabama's math skills bridge program E-MAP has seen a number of modifications. One of the most significant changes has been the implementation of ALEKS software. After the incorporation of ALEKS as a component where students competed for slots in the calculus laboratory of E-MAP, each student group showed measurable increases in knowledge gained, with an average math skills increase of 18%. Since inception, E-MAP has expanded to the College of Engineering at Alabama A&M University through the use of distance learning techniques.

***Index Terms*—Artificial Intelligence Math Skills Learning Programs, Engineering Math Preparation, Minority Student Engineering Preparation, and Pre-Calculus and Calculus Readiness.**

I. Introduction

Over the course of human history, many discoveries have advanced thinking to higher plains. However, in the development of mathematical theory, a major advancement beyond Hellenistic understanding was the development of the Calculus. In ancient times the Latin word "calculus" referred to small counting stones such as on an abacus. These stones form the framework of basic mathematical understanding. Today we have artificial intelligence (AI) technology for advancing mathematics understanding in a way never before achieved. The software Assessment and Learning in Knowledge Spaces (ALEKS), an artificial intelligence system,, is intended to form a basic framework of understanding for mathematics concepts. A growing number of high schools and institutions of higher learning have implemented ALEKS successfully into their classrooms. This paper will describe the implementation of ALEKS as part of a summer bridge program for building student skills at The University of Alabama's College of Engineering called the Engineering Math Advancement Program (E-MAP).

II. The Problem

Overall the Calculus pass rate is 64% at the University of Alabama (UA) and the average withdrawal rate is 20%. However, with a 2007 STEM (Science, Technology, Mathematics, and Engineering) enrollment of 2,406 undergraduate students (11.4% of the total), those not passing Calculus, along with those that withdraw, represent a significant number. UA student retention statistics showed that less than 33% of incoming engineering freshmen were retained in the program through graduation. This is 23% higher than the national average of 52% for similar programs [2]. Analyses indicate that the primary reason for low retention is an inability of incoming freshmen to perform well in first-year calculus classes. Additionally, low performance in calculus was found to impact upper-level engineering

[1] This work sponsored by the National Science Foundation. Acknowledgement to follow.

classes. Math Department staff at UA have linked Calculus grades with long-term attrition in STEM fields. Since early success in Calculus is critical to STEM areas and to combat this deficit, UA developed a unique informal, interactive, and interdisciplinary five-week summer residence class called the Engineering Math Advancement Program (E-MAP) sponsored by the National Science Foundation to ensure incoming freshmen are calculus ready. The program, initiated in 2005, aims to increase retention in engineering by preparing incoming engineering students 1) to do well in calculus and 2) to excite them about engineering. E-MAP also introduces students to hands-on "Living-Lab" experiences, field trips and a community service project led by professional engineers.

Figure 1 is a chart showing student math skill preparation on entering the E-MAP bridge program. E-MAP targets students in the Math Placement Test (MPT) range between 310 and 440. This is the range of students placing into pre-calculus.

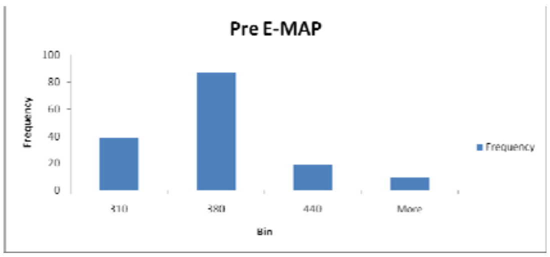

Figure 1: Pre E-MAP bin rankings by MPT score according to math class assignment: 310 and below – Math 100 (Intermediate Algebra); 311 to 380 – Math 112 (Precalculus Algebra); 381 to 440 – Math 115 (Precalculus Algebra and Trigonometry); Above 440 – Math 125 (Calculus I)

III. THE SOLUTION

Over the past four years, E-MAP has seen a number of improvements. One of the most significant changes has been the implementation of ALEKS (Assessment and

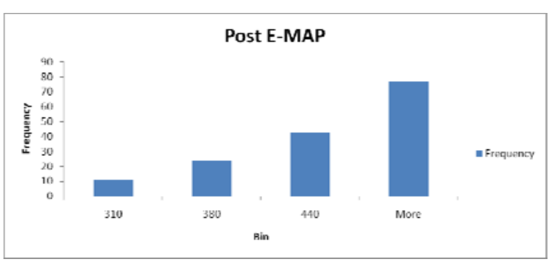

Figure 2: Post E-MAP bin rankings by MPT score according to math class assignment: 310 and below – Math 100 (Intermediate Algebra); 311 to 380 – Math 112 (Precalculus Algebra); 381 to 440 – Math 115 (Precalculus Algebra and Trigonometry); Above 440 – Math 125 (Calculus I)

LEarning in Knowledge Spaces) software. As a result, Post E-MAP MPT scores measured an improvement in student math skills of 18%. [3,4,5,6]

IV. OVERVIEW OF ALEKS

ALEKS software is an AI-based learning system that: (1) targets gaps in individual student knowledge; (2) contains tools for assessment and personalized learning to strengthen student skills; (3) gives extensive content flexibility; (4) has robust course management with automatically gradable homework and quizzes; and (5) provides unlimited online access.

ALEKS, an NSF-funded, web-based AI assessment and learning system developed by researchers at the University of California and New York University, built around knowledge space theory, was first introduced into the program in Year 4 as a successful pilot program. It will now be the focus of morning summer sessions and evening sessions during Year 5 of E-MAP. ALEKS uses adaptive questioning to quickly and accurately determine exactly what a student knows and doesn't know in a course. ALEKS then instructs the student on the topics he or she is most ready to learn. As a student works through a course, ALEKS periodically reassesses the student to ensure that topics learned are also retained. ALEKS courses are very complete in their topic coverage and ALEKS avoids multiple choice questions. A student who shows a high level of mastery of an ALEKS course will be successful in the actual course he or she is taking [7].

ALEKS keeps server statistics that measure the learning success of all students, namely how often they succeed at learning a topic that ALEKS offers them as "ready to learn." When ALEKS determines that a student is ready to learn a topic, the student is able to learn it a very high percentage of the time. In the small percentage of cases where the student is initially unsuccessful, the topic is presented again to the student later on. Because of the artificial intelligence in ALEKS, students are almost always successful at learning the material ALEKS offers them. The level of instructor involvement does not generally play a significant role. The average historical learning rates with ALEKS are approximately 90%.[7]

Within E-MAP, each day, students work through ALEKS answering questions pertaining to their knowledge of concepts necessary for pre-calculus and calculus. Understanding is evaluated by the ALEKS AI engine, addressing problem areas keeping students from advancing. This information is linked to an adaptive learning and lecture campaign for class instructors. Individual instruction is then given to smaller groups based on their level of understanding. A student's knowledge is then re-assessed, allowing him or her to move forward individually or to be given more instruction in any given concept area as the need arises.

Since there is a link between retention in STEM fields and math achievement, the E-MAP targets increasing math proficiency with incoming students to both the math department and the College of Engineering staff. Specifically, it is designed to find and ensure that students who would otherwise struggle during their early math courses have sufficient tools and instruction to overcome any math deficit. The key tool making this possible is the ALEKS Program. ALEKS is useful in providing an intelligent, interactive platform for both instruction and assessment. Heretofore, the best method available to the instructor was through testing. In large classroom sections of introductory math, the student teacher ratios prevent healthy intrapersonal relationships between individual students and instructor. Thus, students may experience difficulty only revealed to an instructor two or three times during the term. By that time, critical understanding and knowledge may be beyond the reach of the student: it is hard for them to "catch up." [8]

In most major universities, math students account to themselves with reading and research topics outside of the classroom. Classroom instruction is reserved for lecture and it may not be possible to press fine detail, logic or procedural mechanics to move stepwise through all given math problems. Under this model students struggle and some fall by the wayside unable to develop discipline necessary to overcome things they perceive to be difficult. Other barriers to communication may also exist, preventing the embedding of a deep understanding of math into potential STEM-destined students. In short, the students do not know what they do not know and without close personal instruction, or personal discipline that needs to develop, may never know. Negative influences, such as poor achievement marks or a feeling of hopelessness and confusion, begin to pressure and students move on to other areas.[8]

V. How UA Uses ALEKS

A transformed classroom model may be the remedy. The University of Alabama Math Department has made progress by reducing the student/teacher ratio so that student/teacher interactions can occur more frequently and the discipline model can develop over time with the instructor's encouragement. Still it is evident that improvement can still be made, and must be made with respect to large influxes of freshmen students. This is the core need for the interactive learning model now possible, in part, through ALEKS. In deploying ALEKS, students essentially are given their own personal instructor or tutor that allows self-paced advancement not previously possible. However, ALEKS can still be viewed as only a tool, and not a replacement for human interaction. Thus the E-MAP couples the traditional classroom model of student/teacher/test to "smart" systems that feed material to students on an individual basis. The real key to success with this program, however, is the ALEKS/Instructor interaction.

As students access and use ALEKS, the AI builds an electronic knowledge base about each particular student, assessing their ability in real-time, and tracking cumulative deficits. This database becomes a powerful tool for instructors to track progress and tailor individual or small group instruction on topical areas to move forward to the next level. Students need not be held back or burdened by instruction to larger groups on material they already understand or are not ready to learn. However, material that is causing consternation with the group or individual is revealed and more time can be dedicated to problem areas. Conjunctively, ALEKS invariably allows for the development of another important life skill: discipline. In traditional classroom models, students complete material outside of the classroom. This "exo-work" competes with outside societal influences or class work and sufficient time may not be dedicated by the student to master the material. It is painfully obvious that not many mathematics textbooks make the national best-seller list for a reason: some individuals find them dry and boring. Knowledge available does not get assimilated. To counter, the E-MAP classroom model forces students to enter into a learning session, not a study session. The interactive AI engine evaluates and quizzes students as they move through material, establishing markers and signposts signaling student advancement. Students must set aside time and cannot advance through the course without it. Instructors know if students are advancing by looking at tabulated data.

VI. Student Impact Data

On average 30% of incoming UA freshmen place into calculus, 10% place into remedial math and 60% are the E-MAP target group. Students who enroll in pre-calculus algebra or trigonometry are 2-3 semesters behind in the freshman program of study. In its fourth year, results indicate E-MAP has helped a majority of students in engineering-math preparedness. Math Placement Test (MPT) data show that 84% of participants skipped at least one math course and 41% 2-3 courses. Statistical analyses were performed and confirmed that the results are statistically significant at the 5% level, and provided very strong evidence to conclude that the mean of pre and post E-MAP students' grades are not equal. At this level of significance, the data proved that, on average, post-program grades (GPA 79.7) are greater than pre-program grades (GPA 56.6). Approximately 30% of participants have been minority and women students. Female averaged scores were higher compared to male scores, the first year showing a significant difference (up to 10 points) in math scores.

Table 1: Improvement of math scores within MPT subgroups after E-MAP using ALEKS.

Pre EMAP MPT Group	% of Total Students	Median Score Increase
310 Group	25%	48.0%
380 Group	56%	30.0%
440 Group	12%	6.1%
>440 Group	6%	-2.7%

E-MAP however was designed to impact students in the pre-calculus range MPT between 310 and 440. Students scoring higher have not benefited. See Table 1. ALEKS implementation addressed this problem by targeting individual student skills sets, something that was not previously feasible through the E-MAP program.

VII. Program Expansion

A common finding is that black student math skills lag behind those of whites and other ethnic groups in the U.S. [9]. Disparities start as early as kindergarten and persist across grades, and in some cases widen over time (www.jbhe.com/features/49_college_admissions-test.html). Reasons given for student disparity varies, but focus is placed on academic knowledge and skill between students from various racial groups [9].

One study performed at the University of Memphis, a large urban institution of higher learning, indicated the effectiveness of using the ALEKS online intelligent tutoring system. ALEKS was successful in closing racial score gaps in an undergraduate behavioral statistics course [10].

Similar in design to the E-MAP program at UA, the study compared students using the traditional lecture format with those using ALEKS. In the lecture format, the traditional racial gap was replicated: black students (n = 118, M = -.49) had a significantly lower average standardized grade than did their white counterparts (n = 259, M = .20). However, for the ALEKS students, the

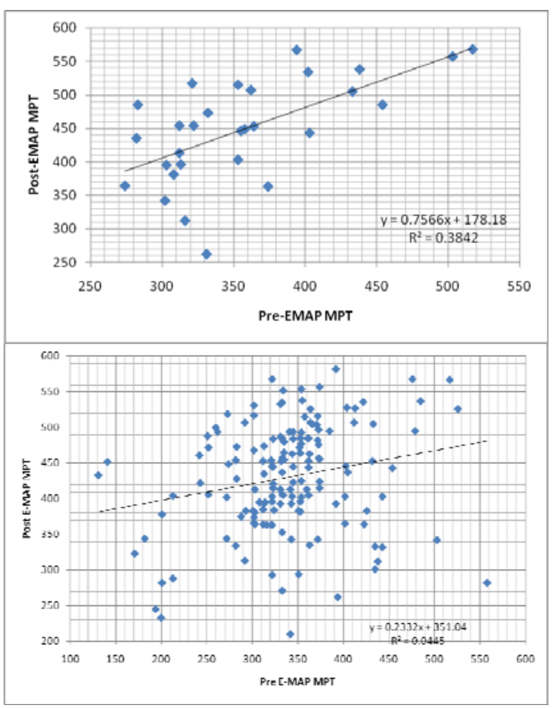

Figure 3: Above: Post-EMAP with ALEKS. Below: Regression analysis of Pre and Post-EMAP MPT scores for all classes between 2005 and 2008.

standardized grade for black students (n = 35, M = .03) was similar to that of their white counterparts (n = 61, M = -.03). Furthermore, black students using ALEKS (n = 35, M = .03) had a significantly higher average standardized grade than did their black counterparts in the lecture sections (n = 118, M = -.49) [9].

For this reason, the Alabama Experimental Program to Stimulate Competitive Research (ALEPSCoR) has been working with the University of Alabama E-MAP team and collaborators at Alabama A&M University (AAMU) and Tuskegee University. Through a seed grant AAMU is currently implementing a freshman math skill building program within their College of Engineering. Tuskegee University has applied for seed funding for the same. Both AAMU and Tuskegee University are Historically Black Colleges and Universities (HBCU's) with aggressive minority advancement programs and are examining data and options for increasing student retention.

VIII. Plans for Alabama A&M

During the 2008-2009 school year Alabama A&M University's Electrical Engineering Department introduced a pilot EMAP program. Students enrolled in EE 101, Introduction to Electrical Engineering, are taught basics using a standard introductory text book and mathematics through E-learning with the UA. The text includes math skills needed to succeed in Electrical Engineering. Materials are presented through both a typical lecture format, hand-on exercises, and tutoring. Students were provided pre and post math skills tests. Out of 100, the average pre test score was 28. Only one student scored at a C level or above. The post test score average improved approximately 5%, with one student scoring a perfect 100. Other student scores were failing. Nearly 50% of the student post scores decreased. AAMU EMAP faculty are discussing with UA engineering and mathematics faculty and ALEKS developers best practices for incorporating ALEKS into their program for the upcoming year for improving understanding.

IX. Evaluation and Conclusions

Studies indicate the value of online AI systems such as ALEKS in preparing students for college course work required to excel in Science, Technology, Mathematics, and Engineering (STEM) areas. According to the No Child Left Behind Act [11], educating a well prepared diverse workforce is critical in solving many of the problems we face. AI infusion into the UA E-MAP is proving to be useful in this endeavor. Additional papers are planned after the 2009-2010 programs have ended. We are at an exciting stage with technological advances, particularly in software engineering and formal methods. What are needed now are an experimentation, integration and application.

ACKNOWLEDGMENT

This work was sponsored by the National Science Foundation's Science Technology Engineering and Mathematics Division. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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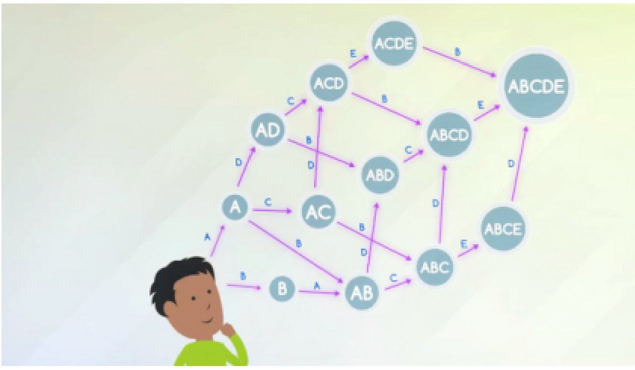
Smart ALEKS

Posted on April 10, 2013

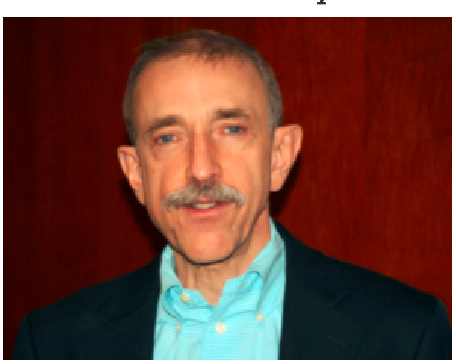
An in-depth look at a Web-based learning and assessment program like no other

INTERVIEW | by Victor Rivero



Imagine a Web-based learning assistant that provides students with individualized and highly-targeted instruction in a variety of subjects. By assessing a student's current knowledge in a subject, it would be able to deliver only the topics that the student is ready to learn. It's real, it's very smart, and it's called ALEKS — an acronym for **A**ssessment and **LE**arning in **K**nowledge **S**paces – named by the developers for its basis in Knowledge Space Theory – a scientific theory that was originated in the early 1980s by cognitive scientists and applied mathematicians at New York University and The Free University of Brussels. It's a web-based learning and assessment program that uses artificial intelligence (AI) and adaptive questioning to provide individualized instruction to each student. It begins by posing 25-30 open-ended, algorithmically generated problems to assess precisely which topics the student knows, doesn't know, and which topics the student is ready to learn next. At the conclusion of the individualized initial assessment, ALEKS provides students with a user-friendly, color-coded pie chart that shows which topics the students are ready to learn right now. ALEKS then enables adaptive learning in which the student selects among the topics he is ready to learn. Whenever a student learns a new topic, ALEKS updates the student's knowledge state and the set of topics he is ready to learn. ALEKS periodically re-assesses the student to verify and solidify content mastery. Research shows this type of "retrieval practice" significantly enhances long-term retention. In essence, "ALEKS is a cycle of learning and assessment," says Wil Lampros (*pictured left*), CEO of ALEKS Corporation, the team of more than 150 content writers, editorial and production staff, software engineers, computer programmers, mathematicians, mathematical cognitive scientists, R&D professionals, business professionals and support staff that make ALEKS work. Here, Wil provides a view of a company with tremendous depth on the leading edge of learning technologies.

Victor: What is the history and some background of your company?



Wil: ALEKS began in 1992 as a project at the University of California to use Knowledge Space Theory to build an intelligent learning and assessment system with major funding from the National Science Foundation. Knowledge Space Theory was developed by our Chairman and other scientists and mathematicians to address a critical need: namely, the need to move from assigning each student a simple one-number score (or at best, a few "sub-scores"), to enabling topic level analysis of individual student knowledge.

The ALEKS project was extremely successful and produced a fully functional web-based learning and assessment technology for math in 1996. Shortly thereafter, the University of California licensed the ALEKS technology to ALEKS Corporation, which was founded by the cognitive scientists and software engineers who created it. After I joined the company in 1998, ALEKS Corporation opened for regular business with four employees in 1999. Now we are a company of over 150 employees, and we help over one million students succeed each year in math, science, business and behavioral science.

What we're most excited about right now is releasing ALEKS course products for Apple's iPad and other popular tablets.

Victor: How is ALEKS unique from other Web-based learning systems?

ALEKS®

Wil: ALEKS is unique because its sophisticated technology uses pinpoint accuracy based on scientific theory and massive data to ensure the student is always working on topics she is ready to learn or needs to review, and it uses algorithmically generated open-response questions, and user-friendly input tools – avoiding multiple-choice. In addition, it is a cycle of learning and assessment that maximizes learning and retention of course material.

Using Knowledge Space Theory and free-response questions, ALEKS is able to provide precise, detailed and comprehensive assessment and highly personalized learning. ALEKS accurately determines, at the atomic level, precisely which topics a student has mastered, has not mastered, and which topics the student is ready to learn next. This information is used to enable students to learn more efficiently, and saves them from boredom and frustration. Students who use ALEKS engage with the subject matter because they are always working on what they are ready to learn.

Each time a student masters an additional topic, ALEKS immediately updates the student's knowledge state and provides the student with a new list of topics she is ready to learn. The result is a continual re-optimization of the student's learning path.

Victor: What does "ready to learn" mean when it comes to ALEKS or any other online learning system?

Wil: In ALEKS, the student is always permitted to choose which topic to work on, but only from among the topics she is ready to learn. "Ready to learn" means exactly what it sounds like: "Will the student be able to master that topic if she works on it right now?" We keep statistics on ALEKS' success in determining whether a student is truly ready to learn a topic in order to evaluate and improve our content and artificial intelligence engine. When ALEKS provides a specific topic to a student as "ready to learn," on average the student successfully masters that topic well over 90 percent of the time. This is what we mean by "ready to learn," and this is what makes the program so powerful and efficient. With ALEKS, students always work on what they are ready to learn right now.

Victor: Tell me about who your customers are in the K-12 market and what products you have to serve them.

Wil: Our customers comprise a wide variety of public, private, and parochial schools; urban, suburban and rural; large and small; using ALEKS as "core/basal" and as a supplement. We have customers reporting hundreds, if not thousands, of successful implementation approaches. We also have many homeschool students using ALEKS.

Our principal K-12 course products currently cover elementary school math through PreCalculus, as well as courses that support intervention, state-specific exit exams and end-of-course exams, and AP Chemistry and Statistics. Our courses cover the entire math curriculum for each grade and are correlated to the Common Core Standards, as well as individual state standards.

We also have robust intervention products for middle school and high school that can be used with students who are substantially behind grade level. For example, for the very large number of students who are significantly behind when they reach Algebra 1 in high school, we offer several different approaches, including products highly focused on the core pre-requisites for Algebra 1, a course that comprehensively covers all the Foundations of High School Math, and a two-course Algebra 1 approach with broad, comprehensive coverage of the Common Core Standards.

Teachers are essential to effective student learning. ALEKS does not replace teachers or parents. What we do is provide the best set of tools we can so that each student has completely individualized learning, and the teacher has vast amounts of detailed, formative, instructionally-actionable information.

Victor: How is what ALEKS does in higher education different than in K-12?

Wil: The technology, essential AI design, and much of the content is the same for similar subject areas in our higher education and K-12 course products. However, our product set and the AI for each course are finely tuned to the standard courses in each respective market and the student populations being served.

Victor: How does assessment work in ALEKS? Is it different than in other self-paced online learning programs?

Wil: Assessments in ALEKS are based on Knowledge Space Theory. There are no question banks in ALEKS. The problems used for assessments are drawn directly from the curriculum for the course. Also, remember that ALEKS avoids unreliable multiple-choice questions. Questions in ALEKS are open-response, and algorithmically generated, as unique instances of each of the topics in the course.

Each student begins her ALEKS experience with a brief initial assessment. After the student answers each question, ALEKS updates its artificially intelligent representation of the student, and bases the next question on the student's answers to all the previous questions. This enables ALEKS to determine which of the vast number of knowledge states the student belongs in, and what she is ready to learn.

Victor: Are all of your offerings in math? What other content areas does ALEKS cover in K-12 and higher education?

Wil: Very roughly half the students using ALEKS are in K-12, and half are in higher education.

In K-12, our course products cover grades 3-12 math. We also have products to help K-12 students in AP Chemistry and AP Statistics, as well as a small number of business courses for high school students.

In higher education, we have all the popular college math classes below Calculus. Over the last few years, we began to make Chemistry courses available. We now have terrific courses for General Chemistry, adoptions of which are growing very rapidly at major universities. We also have excellent offerings to prepare students for General Chemistry. In addition to our math and chemistry offerings, we also have three "flavors" of statistics, as well as Financial Accounting and Business Math.

Many colleges use ALEKS as a key component of one or more of the courses in their math programs. These customers often have dramatically improved student learning outcomes, increasing the pass rates, for example from roughly 50 percent to over 75 percent.

Victor: Tell me how Artificial Intelligence works in ALEKS? How is it different from adaptive learning?

Wil: The science behind ALEKS is a significant departure from standard psychometric theory, which originated in the late nineteenth century and still forms the basis of most testing and adaptive learning systems. As I mentioned, ALEKS uses Knowledge Space Theory, which functions as a form of artificial intelligence, and also enables ALEKS to adapt to each new student response in both learning and assessment. We have materials on our web site explaining the science behind ALEKS, including a great new video called "How ALEKS Works": http://www.aleks.com/video/how_aleks_works

One way of understanding ALEKS AI is as a scientifically advanced "cousin" of a "knowledge graph." The idea is that there may be a map, or "graph," of how concepts are related to each other in a particular context. You hope that you can create a graph that is complete enough to enable you to draw inferences from what you think the student already knows, to other things she might also know or be ready to learn.

In ALEKS, the basic element of the graph is not an individual concept or topic, but a "knowledge state", that is, the combination of topics that might constitute an actual state of student knowledge in a subject. We use "big data" to build knowledge spaces, which map the relations among the knowledge states, or feasible states of student knowledge. These knowledge spaces enable ALEKS to accurately determine which individual topics the student has already mastered, and which ones she is ready to learn.

Victor: How do ALEKS's products prepare students to meet the learning of Common Core? What role does technology play in that support?

Wil: At the student level, ALEKS products cover the entire subject matter of the K-12 course. In other words, we have always attempted to satisfy as high a percentage as possible of all 50 states' curriculum standards. In our most recent courses, we try to satisfy all of the Common Core Standards. Algebra 1, for example, released during the summer of 2012, satisfies 100 percent of the Common Core.

At the instructor level, we have extremely robust reporting and student group formation tools that measure, down to the atomic level, the precise degree of each student's mastery of each of the many topics covering each standard. This provides extensive, extremely detailed, formative, instructionally-actionable information at the individual student and topic levels. These tools permit the instructor to determine precisely which students need help with which topics and standards, enabling the teacher to target the most effective and efficient strategies for Common Core mastery.

Victor: What kind of response do you get from educators about the effectiveness of ALEKS in the classroom?

Wil: Many educators report significantly improved learning outcomes on standardized test scores. They also report an increase in the percentage of students who score at proficient or advanced level, and in the percentage of students who improve their proficiency category from one year to the next. For interested readers, we have special pages for success stories and implementation strategies on our web site (www.aleks.com) in both K-12 and Higher Education Math.

To pick a common situation, the average middle school math teacher may have a group of students who are at drastically different grade levels; some may be far below grade level, while others are far above it. However, even students at the same grade level all have widely varying gaps in their prerequisite knowledge. We call this the "Swiss Cheese Effect," because all students arrive in a class with a different set of holes (or gaps) in their background knowledge.

Because of the program's ability to determine which topics a student has mastered and precisely which topics the student is ready to learn, ALEKS has the unique ability to find and fill each individual student's gaps in prerequisite knowledge, enabling the student to progress on a much more solid foundation. Our customers frequently tell us their students tend to do better in their *next* math class as well.

Educators who use ALEKS in the classroom or lab (such as in a "flipped" or blended learning model) observe that their students are much more likely to be engaged with the material. They report that ADD/ADHD students are often able to concentrate on ALEKS for extended periods of time. Additionally, ALEKS works well to provide an Individualized Education Plan (or "IEP") for every student, and has seen strong results in special education.

Victor: What kind of tools and resources do you provide to teachers? Is there any professional development needed for educators who want to use ALEKS with their students? If so, did you use technology to deliver that professional development?

Wil: ALEKS is intuitive and easy for instructors to get started with immediately.

We offer flexible professional development options for educators both online and in-person. Our dedicated Implementation & Professional Development team offers complimentary daily online trainings where customers can learn more about best practices, as well as pre-recorded training sessions on a variety of ALEKS features.

We also encourage our customers to share ideas and best practices with each other. We have a robust implementation strategies database where ALEKS customers have shared their tips on getting started and implementing the program in a variety of classroom settings. In addition, we have an active ALEKS Community where customers can ask and answer questions with their colleagues.

Victor: Do homeschoolers use ALEKS? Do you offer them special support or resources?

Wil: Homeschoolers have had great success with ALEKS. All of our independent user customers, many of whom are homeschoolers, have access to the full ALEKS course library. So ALEKS can be used by families with children in grades 3-12, as well as by individual students of all ages who wish to learn a new subject, or review or prepare for tests or college. In fact, a great benefit to homeschoolers with older students is that students can receive college credit for American Council on Education (often called "ACE") credit-recommended ALEKS courses. ALEKS QuickTables, a math fact mastery program available in all markets, is particularly popular with younger homeschool students.

A Master Account is provided to parents to allow them to monitor their student's progress in ALEKS. The Master Account contains a variety of reports that detail what their student knows, doesn't know, and is ready to learn right now. Additionally, an attendance report helps track precisely what each student works on and when. Homeschoolers can also use the ALEKS content, and algorithmically generated instances, to provide highly focused quizzes. We find that homeschool customers are up and running on ALEKS very quickly, and if they need additional support, they can access pre-recorded trainings on the ALEKS website.

Victor: What have been some of ALEKS's biggest successes? Greatest challenges?

Wil: There appear to be two key factors in some of our most successful customer implementations. Our customers' greatest successes have occurred when students have used ALEKS for a minimum of three, and preferably four or five hours per week, with meaningful physical or virtual instructor participation in the students' ALEKS learning experience. We have also seen great success where the teacher has taken particular advantage of the robust tools in the ALEKS learning management system. These tools are truly fabulous for educators who want to target their teaching, create homework and quizzes on high-need areas and find and address individual student and group learning issues.

Our biggest challenges fall into two opposite types of institutional or instructor attitudes: one is educators who assume students will do everything necessary to learn math with ALEKS without encouragement, incentive or requirement, and the other is educators who want to micro-manage every student action. We could call these two views: the "get in shape by buying a gym membership" view and the "instructor knows best what each individual student should be working on" view.

We have many options to help address both of these challenges. Most often, work in ALEKS is made a percentage of a student's grade or a source of extra credit. We also have technology that facilitates ALEKS being integrated with more traditional teaching styles, such as modules and textbook chapters. In addition, we have tools to permit homework, quizzing, and testing outside the framework of the ALEKS AI, but with all of the advantages of fully automated grading of non-multiple choice questions. For the most active and involved instructors, there are a vast number of precise, formative reports provided in ALEKS to facilitate the most productive learning management.

Victor: What would you say to a school district that might be on the fence about whether or not to use ALEKS?

Wil: ALEKS offers complimentary, no-commitment pilots to serious potential customers. There are no set-up costs or licensing fees of any kind, so there is no cost to schools or districts that sign up for a free trial. We only ask that institutions give ALEKS a serious and committed trial. Once they experience the dramatically improved learning outcomes that ALEKS provides, they become committed ALEKS customers.

Victor: On to a few broad questions: What are your thoughts on the state of education today?

Wil: Education faces a lot of challenges in the United States today. Schools are overwhelmed by a highly diverse, multilingual population with some students who are years ahead and many who are years behind. Class sizes are often too large for the traditional one-teacher model, which means many students are not being engaged. Often, the best students are slowed down while the weaker students struggle.

Even with these challenges, there are many outstanding, committed, hardworking educators who make a significant, positive impact. In addition, students learn a lot from family members, afterschool programs, classmates, mentors and their community. We know people are resilient; many students overcome a multitude of challenges and go on to eventual success.

In higher education, the United States has become a sort of "university to the world," where many of the most highly trained people in the country and from around the globe come to the U.S. to teach, study, and do research at our universities. Yet, sadly, the average passing rate in most developmental math courses hovers around 50 percent.

In fact, the data show that in both K-12 and in higher education, many students *are* left behind. We see this every day in the dropout rates at high schools and colleges. Many students arrive at school who are years behind in math and other core subjects, or who haven't mastered very basic skills. All too often, they give up.

We can do a lot better.

Victor: What is your outlook on the future of education?

Wil: We are seeing some of the same trends in education today that people have been discussing with regard to healthcare. Reliable, high-quality education is much too expensive for most people, and many of our educational practices in the U.S. do not reliably succeed. Costs are increasing, and class sizes are growing – handicapping even the most talented instructors from effectively providing differentiated instruction. Learning outcomes are becoming more uncertain.

However, there is light at the end of the tunnel. We are beginning to see signs in education of the kind of transformation that has so dramatically affected most other areas of life. That is, as more effective educational technologies become available, it may become possible to affordably provide a high-quality education to the vast majority of students. Educational technology *can* be an extremely effective aid to educators, allowing them to achieve more successful learning outcomes with a higher percentage of the students. At its best, computer software will facilitate the kind of differentiated, one-on-one learning experiences that previously required very small classes or expensive, individual tutoring. In other words, one can imagine a very effective collaboration between experienced educators, and reliable, efficient, and inexpensive technology.

This is the kind of instructor collaboration that ALEKS provides, and the kind of cultural transformation that ALEKS helps to bring about.

Victor: Any final thoughts on education and technology?

Wil: In the design of the first generation of educational technology, the technology was thought of primarily as a device to save educator time via machine grading; little attention was paid to student learning outcomes. These systems tended to be based on multiple-choice questioning, which is far easier to engineer, program and maintain. So-called *homework management* products are examples of this type of technology, but there are many other examples.

But a new generation of technology is emerging. We are now in a position to provide straightforward, non-multiple-choice answer input and machine grading. With the advent of systems that are able to intelligently adapt to individual student needs, we can now provide a student-centric experience in which each student learns at his or her own pace and is far more likely to proceed to mastery. Educators and government entities are beginning to demand acceptable learning outcomes for all students. If our educational institutions begin to routinely require technology that, by individualizing learning, helps each unique student maximize his or her potential, we can see the potential for a far brighter outcome in education.

We think ALEKS is part of this solution.

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Victor Rivero tells the story of 21st-century education transformation. Get your story told through case studies, white papers and other materials you can share at trade shows and on your website. Write to: victor@edtechdigest.com

This entry was posted in cool tools, interviews and tagged AI in education, ALEKS, assessment system, content mastery, individualized learning, Knowledge Space Theory, learning and assessment, learning and assessment system, learning assistant, personalized learning, Wil Lampros. Bookmark the permalink.

4 Responses to *Smart ALEKS*

Kenise Knight *says:*

May 3, 2013 at 7:08 am

Our 3-PreCalculus classes are taught using ALEKS exclusively. This is our second year. The strides our students have made is phenomenol. Students no longer have gaps in their education, they have visual evidence of their progression, it continually assesses students on what they do not know, and repeats those topics any number of times. No teacher can do that and get through the curriculum. Our students love math now and they all are successful. Feel free to contact me at kknight@csprings.k12.mo.us

Reply

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xiousgeonz *says:*

April 11, 2013 at 2:11 pm

I work with students using ALEKS. It "provides instruction" that is 100% procedural. Essentially, clicking "explain" shows a student the page from a math textbook with a subskill isolated there. Students like that they can figure out what the trick is for each piece of pie and move on, but where's the concept development? Are there ever references to visual and/or concrete examples? I've yet to find them except in the word problems, and the "explain" for the word problems deals with which numbers to grab from between the words to do stuff to, not understanding what the math means.

Reply

Aleks Alexson *says:*

April 17, 2013 at 3:45 pm

Ahhhhhh. Not another "concepts are all that matters" argument. Please!

The conceptual stuff is available in some courses (there is nothing preventing it from being included) but let's get real for a moment: teaching concepts of calculus to a bunch of students who don't know that a log is the inverse of an exponent (for example), how to work problems involving logs (or trigonometry, or geometry, or exponents, fractions, radicals, or quadratics) can be pretty pointless. And believe me, there are a lot of students who don't have the basics down trying to learn "concepts" that can't be clearly understood, are anyway are not useful unless paired with mastery of certain skills.

Teaching concepts is the human's job still (and thank God for that, so you still have something to do, because ALEKS is much better at teaching the basics to large numbers of students than any human). ALEKS gives you access to information you would never otherwise be able to get at scale, very cheaply, and very efficiently.

Use your new knowledge (and your newly competent students) to teach "concepts" yourself.

Reply

John Awunganyi *says:*

April 10, 2013 at 8:43 pm

How can I go about creating a pilot for my school. My principal will want to know what will be the yearly cost and maintenance after the end of the piloting period

Reply

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