University of Texas Rio Grande Valley

ScholarWorks @ UTRGV

Theses and Dissertations - UTB/UTPA

7-2015

A study on Hispanic college students' mathematics anxiety, study habits, and academic performances on mathematics

Luis M. Fernandez University of Texas-Pan American

Follow this and additional works at: https://scholarworks.utrgv.edu/leg_etd



Part of the Higher Education Commons, and the Mathematics Commons

Recommended Citation

Fernandez, Luis M., "A study on Hispanic college students' mathematics anxiety, study habits, and academic performances on mathematics" (2015). Theses and Dissertations - UTB/UTPA. 190. https://scholarworks.utrgv.edu/leg_etd/190

This Thesis is brought to you for free and open access by ScholarWorks @ UTRGV. It has been accepted for inclusion in Theses and Dissertations - UTB/UTPA by an authorized administrator of ScholarWorks @ UTRGV. For more information, please contact justin.white@utrgv.edu, william.flores01@utrgv.edu.

A STUDY ON HISPANIC COLLEGE STUDENTS' MATHEMATICS ANXIETY, STUDY HABITS, AND ACADEMIC PERFORMANCES ON MATHEMATICS

A Thesis

by

LUIS M. FERNANDEZ

Submitted to the Graduate School of
The University of Texas-Pan American
In partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

July 2015

Major Subject: Mathematics

A STUDY ON HISPANIC COLLEGE STUDENTS' MATHEMATICS ANXIETY, STUDY HABITS, AND ACADEMIC PERFORMANCES ON MATHEMATICS

A Thesis by LUIS M. FERNANDEZ

COMMITTEE MEMBERS

Dr. Xiaohui Wang Chair of Committee

Dr. Cristina Villalobos Committee Member

Dr. Tim Huber Committee Member

Dr. Jenq-Jong Tsay Committee Member

July 2015

Copyright 2015 Luis M. Fernandez All Rights Reserved

ABSTRACT

Fernandez, Luis M., A Study on Hispanic College Students' Mathematics Anxiety, Study Habits,

and Academic Performances on Mathematics. Master of Science (MS), July, 2015, 97 pp., 16

tables, 12 figures, 58 references, 30 titles.

Mathematics anxiety has been described as a feeling of apprehension, fear, tension, and

discomfort when confronted with mathematics. Mathematics anxiety has also been shown to

interfere with mathematics performance; therefore, for our research we investigated what

portions of individuals seem to suffer higher levels of mathematics anxiety and to what extent

they are affected by it. We also investigated the study habits of the students and how these affect

their mathematics anxiety levels and overall mathematics performance. Our data was obtained

from Hispanic undergraduate students (n=405) who took Elementary Algebra (Math 1300),

Intermediate Algebra (Math 1334), College Algebra (Math 1340) or Elementary Statistics (2330)

in Spring 2015 at the University of Texas Pan-American. Our mathematics anxiety score was

obtained from the Mathematics Anxiety Rating Scale-Brief (MARS-B), a 30-question survey

with 5 levels of agreement.

Keywords: Mathematics Anxiety, Study Habits, Hispanics

iii

DEDICATION

The completion of my master's thesis would not have been possible if it was not for the love and support of my family, especially my parents. Their words of encouragement kept me going further at moments where I felt that I was going to give up. For that and much more, thank you mom and dad.

ACKNOWLEDGMENTS

First and foremost, I would like to thank Dr. Xiahoui Wang, chair of my thesis committee, for her words of wisdom and tremendous patience throughout my graduate studies. The most valuable lesson that I learned from her was on how to become an independent learner. One does not need to be in a classroom to learn something new. We can expand our minds at our own will as long as there is passion in what we do and we always stay hungry for more knowledge.

I would also like to thank my thesis committee Dr. Cristina Villalobos, Dr. Tim Huber, and Dr. Jenq-Jong Tsay. Not only were they exceptional professors but their incredible passion towards teaching also inspired me to pursue a doctorate's degree and become a professor myself. A special acknowledgement goes to Dr. Christina Villalobos for encouraging me to pursue my master's and doctorate's degree. I would not have experienced graduate school if it was not for her support and mentorship.

Lastly, I would like to thank all the instructors and close friends that helped me with the completion of my thesis. They are Ms. Madhavi Devanaboina, Dr. Selma Mahmood, Mr. Guillermo Garza, Ms. Shuxia Li, Mr. Hugo Olvera, Ms. Zaena Zamora, Mr. Vicente Valle, Mr. Alejandro Martinez, Mr. Martin Corona, Mr. Aaron Saenz, Mr. Alan Gonzalez, and Mr. Eduardo Corona.

This work was supported by the U.S. Department of Education under UTPA-MATH Graduate Assistance for Areas of National Need (GAANN). (Grant # P200A120256

TABLE OF CONTENTS

	Page
ABSTRACT	iii
DEDICATION	iv
ACKNOWLEDGMENTS	v
TABLE OF CONTENTS	vi
LIST OF TABLES	viii
LIST OF FIGURES	X
CHAPTER I. INTRODUCTION	1
CHAPTER II. THEORETICAL BACKGROUND	4
2.1 Mathematics Anxiety	4
2.1.1 Causes of Mathematics Anxiety	5
2.1.2 Effects of Mathematics Anxiety	7
2.1.3 Measuring Mathematics Anxiety.	9
CHAPTER III. RESEARCH QUESTIONS	12
CHAPTER IV. METHODOLOGY	15
4.1 Sample	15
4.2 Data Collection	15
4.3 Survey Instrument and Measurements	16
4.4 Statistical Analysis	18
4.4.1 Statistical Model: Linear Regression Model	18

CHAPTER V. RESULTS	25
5.1 Descriptive Statistics	25
5.2 Research Questions Results.	26
5.2.1 Research Question 1 Results	26
5.2.2 Research Question 2 Results	30
5.2.3 Research Question 3 Results	32
5.2.4 Research Question 4 Results	33
5.2.5 Research Question 5 Results	35
CHAPTER VI. CONCLUSIONS AND DISCUSSIONS	42
CHAPTER VII. LIMITATIONS AND FUTURE WORK	48
REFERENCES	50
APPENDIX A	55
APPENDIX B	75
APPENDIX C	88
Student Participation Consent Form	89
Part A. General Information	90
Part B. Study Habits	92
Part C. MARS-B	95
RIOGRAPHICAL SKETCH	07

LIST OF TABLES

P	Page
Table 1. Course descriptions	56
Table 2. List of variables used in the study	58
Table 3. Mean mathematics anxiety scores by all 9 factors	60
Table 4. Comparison of percentile equivalents for Suinn's study and our study of Hispanic students	61
Table 5. Summary of ANOVAs for mathematics anxiety mean score differences for variables classification, courses, and college of major	
Table 6. Summary of independent sample t-tests of mathematics anxiety mean score differences for variables <i>gender</i> , <i>classification</i> , <i>courses</i> , <i>college of major</i> , and <i>school status</i>	63
Table 7. Summary of ANOVAs for mathematics anxiety mean score differences for variable <i>employment status</i>	64
Table 8. Summary of independent sample t-tests of mathematics anxiety mean score differences for variables <i>employment status</i> , <i>grandparents' education</i> , <i>parents' education</i> , and <i>siblings' education</i>	65
Table 9. Results of sequential regression for Research Question 3	66
Table 10. Results of sequential regression for Research Question 4	67
Table 11. List of variables used for Research Question 5 with their corresponding new coding	68
Table 12. Rotated component matrix of the factorial analysis for study habits items	69
Table 13. Rotated component matrix of the factorial analysis for mathematics anxiety items	71

Table 14. Summary of independent sample t-tests of final exam grade differences for binary	
variables gender, classification, courses, college of major, grandparents' education, parents' education, siblings' education, school status, and employment status	72
Table 15. Results of sequential regression for Research Question 5	73
Table 16. Logistic regression model for Research Question 5	74

LIST OF FIGURES

	Page
Figure 1. Deficit Model	6
Figure 2. Inference Model	7
Figure 3. Partial regression plots for all pairs of variables 95% confidence intervals	76
Figure 4. Scatterplot of studentized residuals against unstandardized predicted values within two standard deviations away from the mean	78
Figure 5. Histogram for normality of standerized residuals	79
Figure 6. Partial regression plots for all pairs of variables with 95% confidence intervals	80
Figure 7. Scatterplot of studentized residuals against unstandardized predicted values within two standard deviations away from the mean	82
Figure 8. Histogram for normality of standardized residuals	83
Figure 9. Partial regression plots for all pairs of variables with 95% confidence intervals	84
Figure 10. Scatterplot of studentized residuals against unstandardized predicted values within two standard deviations away from the mean	
Figure 11. Histogram for normality of standardized residuals	86
Figure 12. Histogram showing non-normality of variable <i>course grade</i>	87

CHAPTER I

INTRODUCTION

Mathematical skills are an essential part of everyone's life, especially during adulthood. We use mathematics to budget, tip at restaurants, file income tax returns, and interpret charts and graphs. Aside from technical careers, many non-technical careers in the education, social and behavioral science, and business fields also require a good set of mathematical skills (Preston, 1987). Despite the importance of the subject, it appears that the American population, especially high school students, has accepted the idea that mathematics is an incredibly difficult subject and that the comprehension of basic mathematical ideas is something optional (Geary, 1994; Thompson & Joshua Shearer 2002). The idea is so widely accepted that many see it as part of the American pop culture (Ashcraft, 2002). One particular example is Mattel's 1992 Teen Talk Barbie, a talking Barbie that had 270 pre-recorded messages and whose primary target audience was young girls. This Barbie was probably a gift for many girls who had yet to start grade school yet they quickly learned that, as Barbie told them right out of the box, "Math class is tough!" (Ashcraft, 2002). It is negative messages like these that could start the development of some sort of mathematics-related anxiety within the receptors. Consequently, they could start to develop mathematics anxiety, a specific type of anxiety related to mathematics, that could impede them to properly develop the necessary skills to perform mathematically.

An individual who suffers from mathematics anxiety usually shows symptoms of tension and anxiety that occurs when confronted with a mathematical task varying from ordinary life to academic scenarios (Richardson and Suinn, 1972). Despite the lack of agreement over the specific causes of math anxiety (Gough, 1954), researchers tend to agree on the serious effects of such phenomenon (Ma, 1999). It has been hypothesized that individuals with high levels of math anxiety cannot retain certain information as they try to assess a mathematical task. The thought of failure invades their mind and it is such the anxiety that they forget how to properly handle the mathematical task at hand (Ashcraft, 2002). In an academic setting, Ashcraft and Faust (1994) claim that because of high levels of mathematics anxiety, students develop 'global avoidance.' What this means is that these students will most likely avoid any type of mathematics related curriculum. They will most likely take only the minimum math courses required by their school district, avoiding advanced courses, and it is likely that they could suffer from an academic disadvantage due to the lack of exposure to advanced mathematical material (Ma, 1999). Consequently, they might end up with lower math competence and achievement compared with students with less levels of math anxiety (Ashcraft, 2002), and many would have to resort into taking remedial mathematics courses once at a university level (Hembree, 1990).

Researchers have claimed that the need for remedial mathematics courses could be attributed to mathematics anxiety (Hembree, 1990). What is most alarming about the situation is the high numbers of students having to enroll in such courses. Based on performance scores on placement tests, the vast majority of students enrolling in community colleges need remedial coursework in many subjects, but more noticeably in mathematics (Brown & Niemi, 2007). At a community college in California, over 70% of their incoming class of students failed to meet the performance levels required for entry-level mathematics courses and began their college

experience in remedial mathematics courses (Brown & Niemi, 2007). In the past decade alone, the need for college remedial courses in mathematics has grown to levels never seen before throughout the nation (Hegedorn et al., 1999). Data also shows that students that pertain to minority groups, especially Hispanic students, tend to score at significantly lower levels than Asian American and White students on both ability and mathematics assessment tests (Fox 2005). Because of this, one could infer that Hispanic students could suffer the most from mathematics anxiety but unfortunately research over the matter is limited (Ma, 1999).

It seems that society has accepted the idea that mathematics is hard and that it is ok not to fully understand it, but such ideology could be a serious consequence of a much more serious phenomenon which is mathematics anxiety. It affects the students' performance in mathematics, probably the most in Hispanic students, and because of that, students could suffer from serious academic disadvantages. It is because of the seriousness of this phenomenon as well as the lack of research done on Hispanic college students that our main focus will be to investigate the effects of mathematics anxiety on Hispanic college students. In this study, we will explore the differences in mathematics anxiety levels among Hispanic college students of different gender, academic classification, math courses, and colleges and whether the student is a full-time or parttime student as well being full-time or part-time employed or having no job. Additionally, we will compare the mathematics anxiety levels of students whose family members have attended college before and the effects of having good studying habits on the levels of mathematics anxiety. We will also take into consideration the studying habits of the students and explore the interaction between those habits and the students' mathematics anxiety and performance. Lastly, we will study the overall effect of the previously mentioned student characteristics over their overall mathematics performance, measured by their math course final grades.

CHAPTER II

THEORETICAL BACKGROUND

2.1 Mathematics Anxiety

For many years, researchers have tried to define mathematics anxiety. Dreger and Aiken (1957) described mathematics anxiety as "a syndrome of emotional reactions to arithmetic and mathematics, tentatively designed number anxiety" (p. 344). Similarly, Fennema and Sherman (1976) described math anxiety as "feelings of anxiety, dread, nervousness and associated bodily symptoms related to doing mathematics" (p. 326). Perhaps the most common definition used by researchers comes from Richardson and Suinn (1972) in which they state that mathematics anxiety involves "feelings of tension and anxiety that interfere with the manipulation of numbers and the solving of mathematical problems in a wide variety of ordinary life and academic situations" (p. 551). With all these definitions combined, one can infer that highly math-anxious individuals seem to share the same symptoms: tension, apprehension, helplessness, or fear, and they all seem to be triggered when an individual is confronted with mathematics in one way or another (Wood, 1988; Ashcraft, 2002). Research has also shown that mathematics anxiety seems to interfere with mathematics performance in both adults (Quilter & Harper, 1988) and college students in particular (Betz, 1978; Freary & Ling, 1983). An example of this is found in Hembree's (1990) meta-analysis where college students with higher levels of math anxiety reported an average correlation of -.31 between anxiety and achievement. Despite the extensive

research over mathematics anxiety, it is scarce when it comes to minority groups, especially Hispanic college students (Ma, 1999). It might be possible to infer that Hispanic college students suffer from higher levels of math anxiety compared to their Caucasian peers being that their performance scores in mathematics are usually lower than Caucasians but more research over the matter is required to make such inference (Brown & Niemi, 2007).

2.1.1 Causes of Mathematics Anxiety

Extensive research of mathematics anxiety has been done throughout the years yet the search for a clear cause of such phenomenon has been unsuccessful, usually leading to disagreements among researchers (Gough, 1954). Trujillo and Hadfield (1999) stated that according to Hadfield and McNeil (1994), the origin of math anxiety is attributed to three factors: intellectual, environmental, and personality factors. The intellectual factors consisted of being taught with different teaching styles, negative attitude from the students, and from having low confidence or self-esteem in mathematics (Cemen, 1987; Miller & Mitchell, 1994). Environmental factors include negative classroom experiences like non-participatory math courses, extremely demanding teachers and outside factors like parental pressure (Dossel, 1993; Tobias, 1990). Lastly the personality factors are mainly composed of the effects of high levels of shyness or general low self-esteem. This includes the reluctance to ask questions and viewing mathematics as a field dominated mostly by males (Cemen, 1987; Gutbezahl, 1995; Levine, 1995; Miller et al., 1994). On the other hand, Ashcraft, Kirk and Hopko (1998) claim that the causes for mathetatics anxiety are non-intellectual, being that both successful and unsuccessful students showed similar levels of math anxiety.

Two theoretical models that have been influential in the research of the possible origins of mathematics anxiety are the Deficit Model and the Inferential Model (Ma, 1999). Based on the findings of Desiderato and Koskinen (1969), Mitchell and Ng (1972), and Wittmaier (1979), Tobias (1985) created the Deficit Model, shown in Figure 1, suggesting that poor study habits and testing skills could cause the development of mathematics anxiety. It starts by an individual being presented with a math task. These tasks could be academic like math homework or a math test or they can also be non-academic like calculating the tip of a restaurant's check or being able to quickly know how much change is expected to be received after paying for goods or a service. It is then theorized that if the individual lacks good study habits or has poor testing skills, he will perform poorly in such task. Consequently, feelings of disappointment, tension and embarrassment soon start to develop within the individual and with that mathematics anxiety as well. Culler and Hollahan (1980) also reported that individuals with high levels of anxiety who developed good study skills did better academically than those with poor study skills.

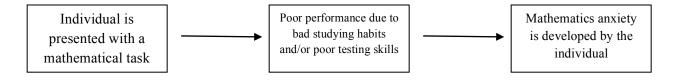


Figure 1. Deficit Model

In the Inference Model, based on the work of Liebert and Morris (1967), Mandler and Sarason (1952), and Wine (1971), researchers claim that there exists a similar linear relationship that causes mathematics anxiety. As shown in Figure 2, an individual first gets confronted with a mathematical task similar to the ones in the Deficit Model. These tasks then trigger memories of bad experiences with math tasks. Examples are remembering low math grades from grade school or negative comments from previous math teachers. These memories then lower the individual's

self-esteem and it is that emotional and psychological disturbance that creates mathematics anxiety.

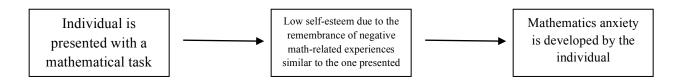


Figure 2. Inference Model

2.1.2 Effects of Mathematics Anxiety

Highly math-anxious students demonstrate an inability to do mathematics (Ma, 1999). They cannot seem to retain information as they try to solve a math problem and it has been hypothesized that this occurs because math anxiety disrupts the ongoing working memory process of the student (Ashcraft 2002). They devote too much attention to their thoughts and worries rather than the task at hand, making it difficult for them to remember basic arithmetic rules (Ashcraft, 2002). Because of their worries of failure, they impulsively answer the question instead of carefully analyzing what has been asked which could lead them into answering the problem incorrectly. Students with high levels of math anxiety also end up with lower math competence and achievement compared with students with less levels of math anxiety (Ashcraft, 2002) and Hispanic students in particular are overrepresented in low math performance being that they score lower in math courses than their Caucasian peers (Brown & Niemi, 2007).

Several characteristics of the relationship between math anxiety and math performance have been most commonly represented by two graphical models (Ma, 1999). One model is often represented as an inverted U-curve depicting a curvilinear relationship between anxiety and performance, also known as the Yerkes-Dodson Law (Hebb, 1955). The second graphical

representation mostly used by researchers shows a negative linear relationship between mathematics anxiety being the independent variable, and mathematics achievement being the dependent variable (Lazarus, 1974). Although both models (U-curve model and negative linear model) are used by researchers, there seems to be a slight incline into the negative linear relationship model because this negative relationship has been described in Quilter & Harper (1988), Betz (1978), Frary & Ling (1983), and Ma (1999).

In addition to low performance in mathematics, both Hispanic and Caucasian students also tend to develop a strong tendency of avoiding any type of mathematics related curriculum (Ashcraft, 2002). They avoid mathematics courses, particularly advanced courses (Ma, 1999), and it is possible that because of such avoidance, they could suffer from an academic disadvantage since they are not being exposed to enough mathematics to have satisfactory levels of mathematics comprehension and competence (Ashcraft, 2002). This could become more noticeable when those students are about to begin their post-secondary education. Once at the college level, it is possible that students with high levels of math anxiety might be assigned a mathematics pre-collegiate basic skill course, or most commonly known as a math remedial course (Brown & Niemi, 2007), courses are designed for students who do not possess the basic mathematical skills to take a college-level mathematics course. After the successful completion of this course they are then permitted to enroll in college-level mathematics courses where the material covered is at a more advanced level, but by going through the remedial route, those students already enter the institution with many disadvantages over students not enrolled in remedial mathematics (Hegedorn, Siadat, Fogel, Nora, & Pascarella, 1999). Because of all of this, those students could be more likely to avoid college majors and career paths that depend heavily on mathematics and consequently this could undercut their math competence and foreclose

important career paths (Armstrong, 1985; Ashcraft, 2002; Betz, 1978; Brush, 1978; Burton, 1979; Donady & Tobias, 1977; Hendel, 1980; Preston, 1987; Richardson & Siunn, 1972; Tobias & Weissbrod, 1980).

2.1.3 Measuring Mathematics Anxiety

During the 1950's, teachers began to observe students' discomfort when confronted with a mathematical task. Soon they realized that it was not just present in their classrooms, but in classrooms around the nation. Consequently, it started to become a topic of interest for many educational researchers. It was not until 1957 when Dreger and Aiken formally introduced the term mathematics anxiety to refer to such phenomenon of discomfort with mathematics. In their definition, mathematics anxiety is the presence of a "syndrome of emotional reactions to arithmetic and mathematics," but despite the difficulties of measuring math anxiety (Wood, 1998), there have been several attempts to address the issue. One of the first instruments to be created for measuring math anxiety was the Dutton Scale (Dutton, 1954; Dutton & Blum, 1968). It was designed with the purpose of measuring feelings towards arithmetic. Other instruments were later developed by Gladstone, Deal, and Drevhdahl (1960) and Aiken and Dreger (1961). Dreger and Aiken (1957) also developed a Number Anxiety Scale specifically made for eight, ninth, and tenth graders. Later, Ainken (1974) developed an instrument with the intentions of measuring enjoyment of mathematics and the value within the subject.

After extensive research and validation, Richardson and Suinn (1972) developed the Mathematics Anxiety Rating Scale (MARS), making it the first comprehensive instrument specifically designed to measure mathematics anxiety. The MARS contains 98 items that are composed of brief descriptions of behavioral situations, for example, "totaling up a dinner bill

that you think overcharged you," that could yield high levels of mathematics anxiety (Richardson & Suinn, 1972). The individual taking the survey then has to evaluate how each item makes them feel using a 5-point Likert scale (1 = Not at all, 2 = A little, 3 = A fair amount, 4 = Much, 5 = Very much). Finally, the mathematics score is obtained by adding the values of all the items, hence the higher the number, the higher the mathematics anxiety level that the student suffers from. Because the MARS was created for college students only, the Mathematics Anxiety Scale for Children (MASC) was later developed by Chiu and Henry (1990).

After the creation of MARS, many variations followed like the Mathematics Anxiety Rating Scale for Elementary school students (MARS-E) (Suinn, Taylor & Edwards, 1988) and the Mathematics Anxiety Rating Scale for Adolescents (MARS-A) (Suinn & Edwards 1982). MARS-E has 26 questions with a 5-point Likert Scale and similarly to the original MARS, the MARS-A has 98 questions with a 5-point Likert Scale. There was also a similar instrument to MARS created called the Fennema-Sherman Mathematics Anxiety Scale (MAS) created for usage on high school students (Fennema & Sherman 1976, Wikoff & Buchalter, 1986). MAS measures feelings of anxiety, dread and nervousness associated with math and it only contains 12 questions, being faster to administer to students. Because of the quickness of MAS, researchers became interested in such tool that they started to implement it on college students, but lack of research about the validity and reliability of MAS quickly led researchers to abandon the usage of MAS completely (Rounds & Handel, 1980). The Mathematics Attitude Inventory (MAI) was later developed by Sandman (1980). It contains 48 questions that are divided into six categories measuring the constructs as (a) perception of the math teacher, (b) anxiety towards math (c) value of math in society (d) self-concept in math (e) enjoyment of math and (f) motivation in

math but, despite the research done with this tool, the validity data has never been reported (Mahmood & Khatoon, 2011).

From all the math anxiety instruments mentioned, the MARS has been the math anxiety instruments most utilized for research and clinical studies (Mia, 1999; Pradeep, 2011; Mahmood & Khatoon, 2011) but despite the usefulness, many researchers have sought for a shorter version of the scale partly to reduce the administration time of the original MARS but yet being comparable to the MARS. Because of such demand, Suinn, the original creator of MARS, and Winston (2003) created the new Mathematics Anxiety Rating Scale-Brief (MARS-B) with only 30 items. With a Cronbach alpha of .96, they confirmed that the MARS-B is comparable to the original MARS (Suinn & Winston, 2003).

CHAPTER III

RESEARCH QUESTIONS

We had conducted a previous study that consisted of data from approximately 1,600 Hispanic undergraduate students from the University of Texas Pan-American between the years 2008 and 2012. Data was collected with the aid of a general questionnaire created by a previous researcher and the Aiken and Dreger (1961) Mathematics Attitude Scale (MAS). The questionnaire provided data on gender, classification, college of major, school status (whether the student was full-time or part-time student), employment status (whether the student had no job or had a part-time or full-time job), parents' education and siblings' education. The MAS on the other hand was composed of 20 items, with items 3, 4, 5, 9, 11, 14, 15, 18, 19, and 20 being positively stated items and the rest were negatively stated items. Positive items denote a positive attitude toward mathematics and they are intended to measure low levels of mathematics anxiety while negatively stated items denote a dislike or fear of mathematics and yield high levels of math anxiety. An example of a positive item is item 9 that states, "The feeling that I have toward mathematics is a good feeling." A negative item like item 13 states, "I approach math with a feeling of hesitation, resulting from a fear of not being able to do math." Students were then asked to rate how much they agreed with each item by using a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Undecided, 4 = Agree, 5 = Strongly Agree). The mathematics anxiety score was then calculated by subtracting the negatively stated items from the positively stated items, ranging from scores between 20 and 100. Based on our findings, there was no

significant difference of mathematics anxiety scores between the two developmental courses. Females showed a significant higher math anxiety level than males (mean difference=4.89, pvalue<0.001, 95% CI: 2.95~6.82), but the effect size (Cohen's d = 0.25) was medium. Nonfreshman students also showed a significantly higher level of math anxiety than the freshman students (mean difference=6.94, p-value<0.001, 95% CI: 4.66~9.21), while the effect size (Cohen's d = 0.36) was medium. The averages of anxiety scores among different colleges were found significantly different (ANOVA p-value<0.001), and the effect size (η^2 =0.06) was medium. The school status, job status, parents' education and siblings' education showed no significant difference of math anxiety levels among them. In order to further investigate this phenomenon, we decided to conduct a new study using a more scholarly recognized mathematics anxiety instrument. We considered more factors like the grandparents' college education level, the students' final exam grades on mathematics courses and overall grade on their mathematics courses. Based on Tobias' Deficit Model (1985), we also decided to investigate the possibility that bad study habits and math skills could yield high levels of mathematics anxiety, hence the students' study habits were considered for this study as well. As such, the following research questions were posed:

Research Question 1: How much do the students' mathematics anxiety levels vary depending on gender, classification, math course, college of major, and school status?

Research Question 2: In what way are students' mathematics anxiety levels influenced by their employment and their grandparents', parents' and siblings' education?

Research Question 3: Is there a relationship between the study habits of a student and their mathematics anxiety levels?

Research Question 4: How does the students' mathematics anxiety in conjunction with their study habits affect their final course grade?

Research Question 5: How are the students' mathematics performance affected by their demographic factors, family's education level, employment status, study habits, and mathematics anxiety?

CHAPTER IV

METHODOLOGY

4.1 Sample

Data was collected during the spring academic semester of 2015 from a total of 405 students at the University of Texas Pan-American, a Hispanic serving institute in the southwest region of the United States. Demographically, 62.7% (n = 254) were female and 57.8% (n = 234) were freshman. The average age of the students was 20.6 years (SD = 4.23). Data also indicated that 82.4% (n = 334) were full time students, 75.8% (n = 307) were non-STEM majors and 48.9% (n = 198) did not have a job. In terms of course enrollment, 28.9% (n = 117) were enrolled in Elementary Statistics, 26.2% (n = 106) in College Algebra, 26.2% (n = 106) in Intermediate Algebra and 18.8% (n = 76) in Elementary Algebra. For the inferential statistical analyses, the sample size varied depending on the completion of individual items on the surveys given to the students. For clarity, this matter will be discussed in more detail for each statistical procedure in the *Results* section in *Chapter V*.

4.2 Data Collection

Before our data collection took place, we selected 20 mathematics courses composed of five Elementary Algebra classes, five Intermediate Algebra classes, five College Algebra classes and five Elementary Statistics classes which we would collect data from. Table 1 contains a more

detailed description of these courses as well as the number of student participants from each course. Survey packets were prepared according to the number of students in each classroom. Once our study was approved by the Institutional Review Board (IRB) at the University of Texas Pan-American, we proceeded with the classroom visitations within a timeframe of two weeks. Each visit was made during the last 25 minutes of class time. During that time, students were educated on what the study was about and were encouraged to participate; their participation was completely voluntarily. Survey packets were then handed to each student and were filled out only by those who agreed to participate in the study. Once the students were done, the survey packets were collected and randomly assigned pseudo codes were attached to them. Data was later recorded on Excel files after all 20 courses had been visited. That same data was then transferred to SPSS for further statistical analysis. Finally, by the end of the academic semester, the instructors of the 20 courses handed final exam grades and overall course grades of only the students who agreed to participate in the study. These grades were ultimately added to the rest of the data set.

4.3 Survey Instrument and Measurements

The survey instrument used in this study was composed of three parts. The first part elicited information about students' gender, age, school classification, college of major, student status (whether the student was full-time or part-time student) and employment status (whether the student had no job or had a part-time or full-time job). It also provided information regarding the education level of their grandparents, parents and siblings. The second part of the survey consisted of a set of 57 items whose purpose was to measure the students' studying habits; items that were obtained from a careful selection of items found in multiple online study habits surveys.

Additionally, these 57 items were broken into 7 different categories (Goals and Attitude, Time Management Skills, Study Environment, Test Taking/Preparation Skills, Note Taking Skills, Reading Skills, Math Skills) and the measurement was possible due to the 3-point Likert-type scale (1= Not True, 2 = Sometimes True, 3 = Always True) that asked students how often they performed "good" study habits. For each category, higher scores yielded better study habits the student possessed whereas lower scores meant the student probably lacked "good" study skills.

For the last part of the survey, we investigated which mathematics anxiety questionnaire had the most recognition among scholars. For that reason we opted for the 30-item Mathematics Anxiety Rating Scale-Brief version (MARS-B) which, as mentioned in section 2.1.3, is a condensed yet reliable version (Cronbach alpha of .96) of the scholarly recognized 98-item Mathematics Anxiety Rating Scale (MARS) (Suinn & Winston, 2003). The 30 items in the MARS-B are composed of brief descriptions of behavioral situations, for example, "receiving your final math grade in the mail," and it prompted the students in our study to choose how frightened those situations made them feel using a 5-point Likert scale (1 = Not at all, 2 = A little, 3 = A fair amount, 4 = Much, 5 = Very much). Adding the values of all the items gave us their mathematics anxiety score, hence the higher the score, the higher the mathematics anxiety that the student suffers from. Additionally, Suinn created a table with percentile equivalents of mathematics scores and states that values above the 75% (mathematics anxiety score of 78) indicate individuals with high levels of mathematics anxiety. A complete copy of the survey given can be found in Appendix C.

4.4 Statistical Analysis

IBM's Statistical Package for the Social Sciences (SPSS) was used for all statistical analysis. The dependent variables were mathematics anxiety score measured by MARS-B, and the students' final exam grade and course grade. The independent variables were gender, classification, courses, college of major, school status, grandparents' education, parents' education, siblings' education, employment status and study habits (i.e. goals and attitude, time management skills, study environment, test taking/preparation skills, note taking skills, reading skills and math skills). Table 2 contains a more detailed description of all the previously mentioned variables. Descriptive statistics were reported for all of the variables. Next, we used student's t-test and ANOVA to assess if there existed a difference in mathematics anxiety mean levels among different genders, age, classifications, courses, colleges, school status, and employment status. Student's t-tests and ANOVA were also used to assess if there existed an association between the mean mathematics anxiety score and the education levels of the students' grandparents, parents, and siblings. Multiple linear regression was used to investigate (1) whether a relationship existed between the study habits of each participant and their mathematics anxiety levels (2) the possible relationship between the students' study habits and mathematics anxiety with their final course grade and (3) the effect of all the students' factors (independent variables) on their final exam grade. Lastly, logistic regression was used to investigate the effect of all the students' factors (independent variables) on their course grade.

4.4.1 Statistical Model: Linear Regression Model

In general, a simple linear regression model is composed of a line with one predictor, also called regressor or explanatory, variable and is written as follows:

$$y = \mu + \epsilon$$
, where $\mu = B_0 + B_1 x$ (1)

Suppose that you have n pairs of observations (x_i, y_i) where i = 1, 2, 3, ..., n. We can then

characterize the these observations as

$$y_i = B_0 + B_1 x_i + \epsilon_i \tag{2}$$

This model requires that the next four assumptions be met:

- 1. The person involved with the experiment must have full control of the repressor variable. This means that x_i , i = 1, 2, 3, ..., n are to be taken as constants; not variables.
- 2. $E(\epsilon_i) = 0, i = 1, 2, ..., n$. This implies that that $\mu_i = E(y_i) = B_0 + B_1 x_i, i = 1, 2, ..., n$.
- 3. $V(\epsilon_i) = \sigma^2$ is constant for all i = 1, 2, ..., n. This implies that the variances $V(y_i) = \sigma^2$ are all the same.
- 4. Different errors ϵ_i and ϵ_j , and hence different responses y_i and y_j , are independent.

And the objectives of such analyses fall under one of the following two categories:

- 1. Can we establish a relationship between x and y?
- 2. Can we predict y from x? To what extent can we predict y from x?

Examples of possible scenarios for researchers to use a simple linear regression model are trying to predict the salary of a teacher based on his or her years of experience and the cost of a vehicle based on the number of previous owners that the vehicle has had.

Now because we could draw many different lines through the cluster of data points, we need a method to choose the "best" line $\mu_i = B_0 + B_1 x_i$ that is "closest" to the points (x_i, y_i) . The method is the *least-squares estimation*, which requires for the errors to be as small as possible. This is possible by minimizing the function

$$S(\beta_0, \beta_1) = \sum_{i=1}^n \epsilon_i^2 = \sum_i (y_i - \mu_i)^2 = \sum_i (y_i - \beta_0 - \beta_1 x_i)^2$$
(3)

with respect to β_0 and β_1 . This approach uses the squared distance as a measure of closeness. To achieve this, we use a symmetric loss function where positive and negative differences are treated the same. Then, the squared error loss function arises.

Taking derivatives with respect to β_0 and β_1 , and setting the derivatives to zero,

$$\frac{\partial S(\beta_0, \beta_1)}{\partial \beta_0} = -2\sum_i (y_i - \beta_0 - \beta_1 x_i) = 0$$

and

$$\frac{\partial S(\beta_0, \beta_1)}{\partial \beta_1} = -2\sum_i (y_i - \beta_0 - \beta_1 x_i) = 0$$

leads to the two equations:

$$n\beta_0 + \left(\sum x_i\right)\beta_1 = \sum y_i$$

$$\left(\sum x_i\right)\beta_0 + \left(\sum x_i^2\right)\beta_1 = \sum x_i y_i$$
(4)

These are referred to as *normal equations*. Suppose that $\hat{\beta}_0$ and $\hat{\beta}_1$ denote the solutions for β_0 and β_1 respectively in the two-equation system (4). Simple algebra shows that these solutions are given by

$$\hat{\beta}_{1} = \frac{\sum x_{i} y_{i} - \frac{(\sum x_{i}) (\sum y_{i})}{n}}{\sum x_{i}^{2} - \frac{(\sum x_{i})^{2}}{n}} = \frac{\sum (x_{i} - \bar{x}) \sum (y_{i} - \bar{y})}{\sum (x_{i} - \bar{x})^{2}} = \frac{S_{xy}}{S_{xx}}$$

$$\hat{\beta}_{0} = \bar{y} - \hat{\beta}_{1} \bar{x}, \quad \text{where } \bar{y} = \frac{\sum y_{i}}{n} \quad \text{and} \quad \bar{x} = \frac{\sum x_{i}}{n}$$
(5)

They are called the *least squares estimates* (LSEs) of β_0 and β_1 , respectively.

Variability among the y_i 's is usually measured by their deviations from the mean, $y_i - \overline{y}$. Thus, a measure of the total variation about the mean is provided by the *total sum of squares* (SST):

$$SST = \sum_{i=1}^{n} (y_i - \overline{y})^2 \tag{6}$$

If SST=0, all observations are the same. The greater is SST, the greater is the variation among the *y* observations. The total sum of squares can be written as:

$$SST = \sum (y_i - \bar{y})^2 = \sum (\hat{\mu} - \bar{y})^2 + \sum (y_i - \hat{\mu}_i)^2 + 2\sum (\hat{\mu} - \bar{y})(y_i - \hat{\mu}_i)$$

$$= \sum (\hat{\mu}_i - \bar{y})^2 + \sum (y_i - \hat{\mu}_i)^2$$

$$= SSR + SSE$$
(7)

Where SSR is the *regression sum of squares* (the variation in the observed values of the response variable explained by the regression) and SSE is the *error sum of squares* (the variation in the observed values of the response variable not explained by the regression).

Lastly, in order to measure the degree of linear association between y and x, we use a descriptive measure called the *coefficient of determination*: R^2 . Before we do so, consider the identity (7):

The ratio

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{8}$$

is used to assess the "fit" of a regression model. It expresses the proportion of the total variation of the response around the mean that is explained by the regression model. R^2 must be in between 0 and 1 where $R^2 = 0$ indicates that none of the variability in the y is explained by the regression model. SSE=0 and $R^2 = 1$ indicate that all observations fall exactly on the fitted line.

In a *multiple linear regression model*, we consider the following model:

$$y = B_0 + B_1 x_1 + B_2 x_2 + \dots + B_p x_p + \epsilon$$
 (9)

This model links the response variable y to several independent variables $x_1, x_2, ..., x_p$. Similarly as the *simple linear regression model*, we must meet the next four assumptions (Warner, 2008) so

that the validity of the procedure is ensured:

- 1. The *Y* outcome variable should be quantitative with scores that are approximately normally distributed. This assumption can be assessed by looking at the univariate distributions of scores on *Y*.
- The relations among all pairs of variables should be linear. This assumption of linearity can be assessed by examining bivariate scatterplots for all possible pairs of these variables.
- 3. There should be no interactions between variables, such that the slope that predicts Y from X_n differs across groups that are formed based on scores on X_{n+1} . This assumption can be checked by grouping subjects based on scores on the X_{n+1} variable and running a separate X_n , Y scatter plot for each group. The slopes should be similar across groups.
- 4. Variance in *Y* scored should be homogeneous across all levels of *X*. This assumption can be assessed by examining bivariate scatter plots to see whether the range of variance of *Y* scores varies across levels of *X*.

Multiple linear regression is best fit when researchers want to predict a single numerical variable from several independent variables. These independent variables can be numerical, dichotomous, or a combination of both. Categorical variables with more than 2 levels are also allowed but they require dummy coding. Real life applications for multiple linear regression are predicting the growth of a certain plant based on the quantity of water and fertilizer received and estimating the cost of a house based on the number of rooms and floors the house has.

Once the model is built, the next step would be optimizing it for the best results. A common way to assess this task is to build variations of the same model, either by dropping or adding variables, and compare their adjusted-R². Techniques that allow us to build such models are normally referred to as *Stepwise Procedures*. These procedures can be broken down into 3 different categories:

- 1. **Forwards selection** starts with an empty model. The variable that has the smallest p-value when it is the only predictor in the regression equation is placed in the model. Each subsequent step adds the variable that has the smallest p-value in the presence of the predictors already in the equation. Variables are added one-at-a-time as long as their p-values are small enough, typically less than 0.05 or 0.10.
- 2. **Backwards elimination** starts with all of the predictors in the model. The variable that is least significant--that is, the one with the largest p-value--is removed and the model is refitted. Each subsequent step removes the least significant variable in the model until all remaining variables have individual p-values smaller than some value, such as 0.05 or 0.10.
- 3. **Stepwise regression** is similar to forward selection except that variables are removed from the model if they become non-significant as other predictors are added.

Forward selection is recommended when researchers want to build a model with the least number of predictors as possible. Backward elimination is best used when the researcher wants to take all the variables into consideration and build a more comprehensive model, even if this one contains a significant amount of predictor variables. Stepwise regression is used when the researcher is looking for the most optimal model, regardless of the amount of predictor variables that will be in the model.

CHAPTER V

RESULTS

5.1 Descriptive Statistics

Descriptive statistics, shown in detail in Table 3, showed that female students had an average mathematics anxiety (MA) score of 86.02 (SD = 22.73) and males had an average MA score of 72.41 (SD = 24.51). Students who were freshman reported an average MA score of 80.03 (SD = 23.89) whereas students who were seniors reported an average MA score of 84.58 (SD = 28.07). Students whose major pertained to the College of Arts and Humanities reported an average MA score of 89.56 (SD = 20.94). On the other hand, students from the College of Science and Mathematics reported an average MA score of 71.54 (SD = 24.01). In terms of school status, full-time students reported an average MA score of 80.38 (SD = 24.43) and parttime students reported an average MA score of 84.61 (SD = 23.23). The average MA score of students whose grandparents, parents, and siblings attended college was 82.38 (SD = 24.09), 78.95 (SD = 23.97) and 80.42 (SD = 23.82) respectively. Lastly, students who were employed full time reported an average MA score of 84.49 (SD = 24.42) but students who were not employed at the time of the study reported an average MA score of 78.12 (SD = 23.09). We also compared the percentile equivalents of mathematics anxiety scores from Suinn with the mathematics anxiety scores of the Hispanic students from our study. Table 4 shows the comparison between both percentile equivalent tables.

5.2 Research Questions Results

5.2.1 Research Question 1 Results

Research Question 1 investigated possible differences of mathematics anxiety scores among students' demographic factors. These included gender, classification, courses, college of major, and school status. ANOVAs and independent sample t-tests were performed. Results for ANOVAs are reported in Table 5 and results for the independent sample t-tests are reported in Table 6.

Gender

An independent samples t-test was performed to assess whether the mean mathematics anxiety scores differed significantly between genders (Males=1, Females=2). Preliminary data screening indicated the mathematics anxiety scores were normally distributed for females but not for males, as assessed by Shapiro-Wil's test (p = .015), but the departure from normality was not judged serious enough to require the use of a non-parametric test. The assumption of homogeneity of variance was assessed by the Levene test, F=0.759, p=0.384; this indicated no significant violation of the equal variance assumption; therefore, the pooled variances version of the t-test was used. Females had a significantly higher anxiety mean score than males (mean difference= 13.61, p-value<0.001, 95% CI: 8.74~18.48), and the effect size (Cohen's d=0.58) was medium.

Classification

Our sample was not evenly distributed for our variable, hence we went ahead and converted the 4-level variable *classification* into a 3-level variable (Freshman=1, Sophomores=2, Juniors or

Seniors=3). Next, a one-way ANOVA was done to compare the mean scores among the 3 levels but there was not enough evidence to state that there was a statistically significant difference. Furthermore, we went ahead and investigated the possible difference among mathematics anxiety levels between two groups, freshman students (Freshman=1) and non-freshman students (Non-freshman=2) but again there was not enough evidence to state that there was a statistically significant difference between them.

Courses

A one-way ANOVA was done to compare the mean scores of mathematics anxiety for the 4 mathematics courses (Elementary Algebra=1, Intermediate Algebra=2, College Algebra=3, Elementary Statistics=4). Preliminary data screening indicated that the mathematics anxiety scores were normally distributed for all levels except Elementary Statistics, as assessed by Shapiro-Wil's test (p = .045), but the departure from normality was not judged serious enough to require the use of a non-parametric test. The assumption of homogeneity of variance was assessed by the Levene test, F=0.543, p=0.653; this indicated no significant violation of the equal variance assumption. The overall F-statistic for the one-way ANOVA was statistically significant, F(3,379)=9.218, p-value<0.001. This corresponds to an effect size of $\eta 2=0.68$ which is medium. Furthermore, all possible pairwise comparisons were made using the Bonferroni procedure. Based on this test (using $\alpha = 0.05 / 4 = .0125$), it was found that Intermediate Algebra had a significantly higher mathematics anxiety mean score (M=90.24, SD=23.25) than Elementary Algebra (M=79.06, SD=23.82), College Algebra (M=80.26, SD=22.24), and Elementary Statistics (M=74.39, SD=24.93). Elementary Algebra, College Algebra, and Elementary Statistics did not differ significantly from one another.

Lastly, we wanted to compare the mathematics anxiety scores between developmental math courses (Elementary algebra=0, Intermediate Algebra=0) and non-developmental math courses (College Algebra=1, Elementary Statistics=1). This was possible by combining the 4-level variable *courses* into a binary variable. We then performed an independent samples t-test to assess whether the mean mathematics anxiety scores differed significantly between developmental mathematics courses and non-developmental mathematics courses. Mathematics anxiety scores were normally distributed, as assessed by Shapiro-Wil's test (p > .05). The assumption of homogeneity of variance was assessed by the Levene test, F=0.010, p=0.922; this indicated no significant violation of the equal variance assumption; therefore, the pooled variances version of the t-test was used. The mean mathematics anxiety score for students in the developmental mathematics courses had a significantly higher anxiety mean score than those in the non-developmental mathematics courses (mean difference= 8.84, p-value<0.001, 95% CI: 4.00~13.68), and the effect size (Cohen's d=0.37) was small.

College of major

A one-way ANOVA was done to compare the mean scores of math anxiety for students that pertained to different *colleges* (College of Arts and Humanities=1, College of Social and Behavioral Sciences=2, College of Business=3, College of Education=4, College of Science and Mathematics=5, College and Engineering=6, College and Health and Human Services=7). Prior to the analysis, the Levene test for homogeneity of variance was used to examine whether there were serious violations of the assumption of homogeneity of variance across groups, but no significant violation was found: F(6, 370)=0.485, P=0.819. Mathematics anxiety scores were also normally distributed for all levels, as assessed by Shapiro-Wil's test (P>0.05). The overall P=0.05.

statistic for the one-way ANOVA was statistically significant, F(6,369)=3.541, p-value=0.002. This corresponds to an effect size of $\eta 2=0.054$ which is small. Additionally, all possible pairwise comparisons were made using the Bonferroni procedure. Based on this test (using $\alpha=0.05$ / 7 = .007), it was found that the College of Education had a significantly higher mathematics anxiety mean score (M= 89.32, SD= 21.66) than the College of Science and Mathematics (M= 71.54, SD= 24.01). The remaining colleges did not differ significantly among them.

Additionally, we wanted to compare the mathematics anxiety scores between STEM colleges (College of Science and Mathematics=1 and College of Engineering=1) and Non-STEM colleges (College of Arts and Humanities=0, Social and Behavioral Sciences=0, Business=0, Education=0, and Health and Human Services=0). This was possible by combining the 7-level *college of major* variable into a binary variable. We then performed an independent samples t-test to assess whether the mean mathematics anxiety scores differed significantly between STEM colleges and Non-STEM colleges. Preliminary data screening showed that mathematics anxiety scores were normally distributed for both STEM and Non-STEM colleges, as assessed by Shapiro-Wil's test (p > .05). The assumption of homogeneity of variance was assessed by the Levene test, F=0.090, p=0.765; this indicated no significant violation of the equal variance assumption; therefore, the pooled variances version of the t-test was used. The mean mathematics anxiety score for students in Non-STEM colleges had a significantly higher anxiety mean score than those in STEM colleges (mean difference=8.28, p-value=0.006, 95% CI: 2.42~14.12), but the effect size (Cohen's d=0.34) was small.

School Status

An independent samples t-test was performed to assess whether the mean mathematics anxiety scores differed depending on the students' *school status* (Full-Time Students=1, Part-Time Students=2) but there was not enough evidence to state that there was a statistically significant difference among those two groups.

5.2.2 Research Question 2 Results

Research Question 2 investigated whether the students' employment status, grandparents' education, parents' education, and siblings' education played a role in their mathematics anxiety levels. Because of this, ANOVAs and independent sample t-tests were performed. Results for ANOVAs are reported in Table 7 and results for the independent sample t-tests are reported in Table 8.

Employment Status

A one-way ANOVA was done to compare the mean scores of mathematics anxiety for *employment status* (Full-Time Employee=1, Part-Time Employee=2, Not Employed=3) but there was not enough evidence to state that there was a statistically significant difference.

Because of this, we went ahead and investigated the possible difference among mathematics anxiety levels between employed students (Employed=0) and non-employed students (No Employment=1). This was possible by combining the 3-level variable *employment status* into a binary variable. We then performed an independent samples t-test to assess whether the mean mathematics anxiety scores differed significantly between them. Mathematics anxiety scores were normally distributed for all levels, as assessed by Shapiro-Wil's test (p > .05). The

assumption of homogeneity of variance was assessed by the Levene test, F=1.358, p=0.245; this indicated no significant violation of the equal variance assumption; therefore, the pooled variances version of the t-test was used. The mean mathematics anxiety score for employed students was significantly higher than the non-employed students (mean difference= 5.47, p-value=0.014, 95% CI: 0.63~10.30), but the effect size (Cohen's d=0.22) was small.

Grandparents' Education, Parents' Education and Siblings' Education

An independent samples t-test was performed to assess whether the mean mathematics anxiety scores differed significantly between students whose at least one parent attended or graduated from college (Yes=2) and those whose parents did not attend or graduated from college (No=1). Preliminary data screening indicated that mathematics anxiety scores were not normally distributed for students whose at least one parent attended or graduated from college (Yes=2), as assessed by Shapiro-Wil's test (p = .037), but the departure from normality was not judged serious enough to require the use of a non-parametric test. The assumption of homogeneity of variance was assessed by the Levene test, F=0.240, p=0.625; this indicated no significant violation of the equal variance assumption; therefore, the pooled variances version of the t-test was used. The mean mathematics anxiety score for students whose parents did not attend or graduated from college had a significantly higher anxiety mean score than those students whose at least one parent attended or graduated from college (mean difference= 4.23, p-value=0.045 95% CI: -0.64~9.10), but the effect size (Cohen's d=0.18) was small.

An independent samples t-test was also performed to assess whether the mean mathematics anxiety scores differed significantly between students whose at least one grandparent or sibling attended or graduated from college (Yes=2) an those whose grandparents or siblings did not

attend or graduated from college (No=1), but there was not enough evidence to state that there was a statistically significant difference.

5.2.3 Research Question 3 Results

A multiple linear regression analysis was conducted in order to investigate the relationship between the students' study habits (i.e. *goals and attitude, time management skills*, *study environment, test taking/preparation skills*, *note taking skills*, *reading skills* and *math skills*) (independent variables) and the students' overall *mathematics anxiety score* (dependent variable).

The total N for this sample was 405 but 45 cases were dropped due to missing data; hence for this analysis, N = 360. Next, despite various transformations attempted on all variables, only five variables were able to show signs of linearity when partial regression plots were inspected as shown in Figure 3. Those variables were: *goals and attitude, time management skills, note taking skills, reading skills*, and *math skills*. The lack of fit test confirmed our assumption of linearity with only those 5 variables (F=2.730, p=.306). Because of this, our sample was now N=369. The assumption of homogeneity of variance was assessed via an inspection of a scatterplot plotting the unstandardized predicted values against the studentized residuals. In this scatterplot, there existed a relatively random display of points, where the spread of residuals appears fairly constant over the range of values of the independent variable, thus providing evidence of homogeneity of variance. Figure 4 contains a more detailed description of such scatterplot. There was independence of residuals, as assessed by a Durbin-Watson statistic of 1.996. Lastly, the histogram of the regression standardized residuals showed that the distribution of residuals followed a bell-shape distribution well enough to support a conclusion that the

residuals are normally distributed. Figure 5 contains a more detailed description of the histogram. With these assumptions met, the validity of our statistical procedure was ensured.

Multiple linear regression was performed using the Backwards elimination with the F-to-remove criterion value set at the probability of F being 0.10. This resulted in the following order of removal: STEP 1, *reading skills*; STEP 2, *note taking skills*; STEP 3, *time management skills*, thus creating a total of four models including the full model. Results of this sequential regression are summarized in Table 9.

Out of the four models from Table 9, the best choice would be Model 4 since it follows the principle of parsimony, which is having a model to be as simple as possible, without containing redundant parameters or factor levels. Overall, Model 4 was statistically significant, adjusted R^2 = .135, F(2, 367)= 29.674, p < .001. To further assess the contributions of both variables individually, the t-ratios for the individual regression slopes were examined. Both variables were significantly predictive of mathematics anxiety scores; results were *goals and attitude*, t(367) = -2.087, p = 0.038; and *math skills*, t(367) = -5.716, p < .001. Additionally, we found that with every one-point increase in: (1) *math skills*, there is an approximate 2.8 point decrease in the students' *mathematics anxiety score*; and (2) *goals and attitude*, there is an approximate 0.7 decrease in the students' *mathematics anxiety score*.

5.2.4 Research Question 4 Results

A multiple linear regression analysis was conducted in order to investigate the relationship between the students' study habits (i.e. *goals and attitude, time management skills*, *study environment, test taking/preparation skills*, *note taking skills*, *reading skills* and *math skills*) and their *mathematics anxiety scores* (independent variables) and the students' *course grade*

(dependent variable). We then had to drop 72 cases being that those students did not take their final exam, dropped from the course, or were missing information for their study habits questionnaire. This made our total sample be N=333.

Next, despite various transformations attempted on all variables, only five variables were able to show signs of linearity when partial regression plots were inspected as shown in Figure 6. Those variables were: time management skills, study environment, test taking/preparation skills, reading skills, and math skills. The lack of fit test confirmed our assumption of linearity with only those 5 variables (F=4.797, p=.109). Because of this, our sample became N=355. The assumption of homogeneity of variance was assessed via an inspection of a scatterplot plotting the unstandardized predicted values against the studentized residuals. In this scatterplot, there existed a relatively random display of points, where the spread of residuals appears fairly constant over the range of values of the independent variable, thus providing evidence of homogeneity of variance. Figure 7 contains a more detailed description of such scatterplot. There was independence of residuals, as assessed by a Durbin-Watson statistic of 1.921. Lastly, the histogram of the regression standardized residuals did not show strong evidence of normality but the regression analysis was done anyway because it is fairly robust to non-normality (Bartlett, 1935; Eisenhart, 1947; Lorenzen and Anderson, 1993; Pearson, 1931). Figure 8 contains a more detailed description of this histogram.

Multiple linear regression was performed using the Backward method with the F-to-remove criterion value set at the probability of F being 0.10. This resulted in the following order of removal: STEP 1, *test taking skills*, thus creating only two models including the full model. Results of this sequential regression are summarized in Table 10.

Out of all the models from Table 10, the best one was Model 2 since it does not contain redundant parameters or factor levels. Overall, Model 2 was statistically significant, adjusted R^2 = .120, F(4, 350)= 11.899, p < .001. To further assess the contributions of all variables individually, the t-ratios for the individual regression slopes were examined. Only the variables time management skills, t(350) = 3.873, p < .001; reading skills, t(350) = -2.527, p = .012; and mathematics skills, t(350) = 4.466, p < .001 were significantly predictive of the students' course grade. Additionally, we found that with every one-point increase in: (1) math skills, there is an approximate 1.7 point increase in the students' course grade; (2) time management skills, there is an approximate 2 point increase in the students' course grade; (3) reading skills, there is an approximate 1 point decrease in the students' course grade; and (4) study environment, there is an approximate 0.6 point decrease in the students' course grade.

5.2.5 Research Question 5 Results

For our comprehensive research question, we wanted to explore the relationship among the students' *gender*, *classification* (freshman, non-freshman), *course* of enrollment (developmental math course, non-developmental math course), *college* of major (STEM, non-STEM), *grandparents' education*, *parents' education*, *siblings' education*, *employment status* (employed, non-employed), *school status* (full-time, part-time), study habits (i.e. *goals and attitude, time management skills*, *study environment, test taking/preparation skills*, *note taking skills*, *reading skills* and *math skills*), and *mathematics anxiety score* (all independent variables) and the students' mathematics performance, that is, *final exam grade* and *course grade* (both dependent variables). Because of this, two models were required to investigate each relationship individually, one for *final exam grade* and another one for *course grade*. Note that along with

numerical variables, we are also dealing with categorical variables as predictors hence why we opted to use the categorical variables with only two levels. We could have created dummy variables and considered all levels of each categorical variable but such action did not seem necessary for the purposes of our study. The distribution for each categorical variable would have also not been well distributed. Refer to Table 11 for more details over the categorical variables used in this regression model and their corresponding re-coding.

Furthermore, in multiple linear regression, there exists a rule of thumb that suggests to have approximately 15 to 20 cases per parameter used in the model to have reliable results and that was not possible with our data given that there was a total of 17 parameters considered and our sample size would not suffice. In order to address this matter, factor analysis was performed on the 57 items that pertained to the 7 variables under study habits. Results showed that the 57 items loaded into 3 factors that measured similar characteristics of students' study habits. These 3 factors became our new study habits variables: (1) academic self-discipline which was composed of 29 items that measured the discipline students have towards their education (2) reading and writing skills which was composed of 14 items that measured how well students read and write and (3) mathematics and test taking skills which was composed of 14 items that measured how well students perform on mathematics and tests in general. Additionally, factor analysis was performed on the 30 items pertaining to the MARS-B. Results showed that the 30 items loaded into two factors, a finding that has been seen in similar studies where factor analysis has been performed on the MARS-B (Suinn & Winston, 2003). Based on those studies, we were able to classify the two factors as two new variables (1) mathematics test anxiety which was composed of 15 items that measured the anxiety individuals experience when they are exposed to any type of mathematics testing and (2) numerical anxiety which contained 15 items

that measured anxiety felt by the manipulation of numbers. A detailed description of the factorial analysis performed on the 57 items of the study habits questionnaire and the 30 items of the MARS-B are found in Table 12 and Table 13 respectively.

Final Exam Grade

A multiple linear regression analysis was conducted in order to investigate the relationship between the students' gender, classification (freshman, non-freshman), course of enrollment (developmental math course, non-developmental math course), college of major (STEM, non-STEM), grandparents' education, parents' education, siblings' education, employment status (employed, non-employed), school status (full-time, part-time), study habits (i.e. academic selfdiscipline, reading and writing skills and mathematics and test taking skills), and mathematics anxiety score (all independent variables) and the students' final exam grade (dependent variable). For this procedure, 156 cases had to be dropped due to missing data, making our total sample N=249. Furthermore, after close inspection of our partial regression plots, linearity was only shown for the variables numerical anxiety, academic self-discipline, reading and writing skills and *mathematics* and *test taking skills*. Figure 9 contains a summary of all partial regression plots. In order to assess "linearity" between our 2-level categorical variables and the students' final exam grade, independent sample t-tests were performed. Based on these results, only variables classification, courses, school status, and employment status showed statistically significant differences in the students' final exam grade, therefore only those categorical variables were considered in the regression model. Table 14 contains the results for all the independent sample t-test. The assumption of homogeneity of variance was assessed via an inspection of a scatterplot plotting the unstandardized predicted values against the studentized residuals. In this scatterplot,

there existed a relatively random display of points, where the spread of residuals appears fairly constant over the range of values of the independent variable, thus providing evidence of homogeneity of variance. Figure 10 contains a more detailed description of such scatterplot. There was independence of residuals, as assessed by a Durbin-Watson statistic of 1.875. Lastly, the histogram of the regression standardized residuals showed that the distribution of residuals followed a bell-shape distribution well enough to support a conclusion that the residuals are normally distributed. Figure 11 contains a more detailed description of the histogram. With these results, our sample became N=315 and the validity of our statistical procedure was ensured. Similarly to previous research questions, multiple linear regression was performed using the Backward method with the F-to-remove criterion value set at the probability of F being 0.10. This resulted in the following order of removal: STEP 1, classification; STEP 2, numerical anxiety; STEP 3, school status; and STEP 4, academic self discipline; thus creating a total of 5 models including the full model. Results of this sequential regression are summarized in Table 15.

Out of all the models given in Table 15, the best one was the last model since it contained a high R^2 and did not contain redundant parameters or factor levels. Overall, our chosen model was statistically significant, adjusted R^2 = .234, F(4, 310)= 24.948, p < .001. To further assess the contributions of the variables individually, the t-ratios for the individual regression slopes were examined. The variables *course*, t(310) = -9.146, p < .001; *mathematics and test taking skills*, t(310) = 3.798, p < .001; *reading and writing skills*, t(310) = -2.083, p= .038; and *employment status*, t(310) = 2.277 p= .023; were significantly predictive of the students' *final exam grade*. Additionally, we found that with every one-point increase in: (1) *mathematics and test taking skills*, there is an approximate 1.2 point increase in the students' *final exam grade*; and (2)

reading and writing skills, there is an approximate half point decrease in the students' final exam grade. In terms of our categorical variables: (1) students in the developmental mathematics courses reported an approximate 20 point decrease in their final exam grade when compared with students in the non-developmental mathematics courses and (2) students who are non-employed reported an approximate 5 point increase in their final exam grade when compared with employed students.

Course Grade

A logistic regression analysis was conducted because of the non-normal distribution, found in the histogram on Figure 12, of the variable *course grade*. In this analysis, we wanted to investigate the relationship between the students' *gender*, *classification* (freshman, non-freshman), *course of enrollment* (developmental math course, non-developmental math course), *college of major* (STEM, non-STEM), *grandparents' education*, *parents' education*, *siblings' education*, *employment status* (employed, non-employed), *school status* (full-time, part-time), study habits (i.e. *academic self-discipline*, *reading and writing skills* and *mathematics and test taking skills*), and *mathematics anxiety score* (all independent variables) and the students' *course grade* (dependent variable). Note that the variable *course grade* was originally a numerical variable but it had to be converted into a binary categorical variable given the nature of logistic regression. Students who scored less than a 60 on their course were coded under "unsatisfactory performance" and students who scored a 60 or higher were coded under "satisfactory performance." The coding was done based on the grading policies from the University of Texas Pan-American.

For this procedure, 139 cases had to be dropped due to missing data, making our total sample N=266. Chi-Square tests indicated a significant association between 1) *student status* and *course grade* and 2) *employment status* and *course grade*, therefore only those categorical variables were considered for the model. The Box-Tidwell procedure indicated that all numerical variables were linearly associated with *course grade*, hence all numerical variables were considered for the model. Lastly, the error terms yielded independence and with this, our assumptions were met given that in logistic regression the independent variables do not need to be multivariate normal, the residuals do not need to be multivariate normally distributed, and homoscedasticity is not needed as opposed to multiple linear regression. With these results, our sample became N=327 and the validity of our statistical procedure was ensured.

Logistic regression was performed using the Backward method where the removal of variables is based on the probability of the Wald statistic. This resulted in the following order of removal: STEP 1, courses; STEP 2, numerical anxiety; STEP 3, mathematics and test taking skills; STEP 4, mathematics test anxiety; and STEP 5, school status; thus creating a total of 6 models including the full model.

Out of all the models given by the sequential regression, the model chosen to have the best fit was the one given after STEP 3 given that it contained a high Nagelkerke R^2 and did not contain a significant amount of redundant parameters or factor levels. Overall, our chosen model significantly predicted *course grade*, Nagelkerke R^2 = .151, $\chi^2(6)$ = 30.80, p < .001, and it successfully classified 83.8% of the cases. To further assess the contributions of the variables individually, the Wald statistics for the individual regression slopes were examined. The variables *academic self-discipline*, Wald statistic equal to 11.812, p = .001; *reading and writing* skills, Wald statistic equal to 10.366, p = .001; and *employment status*, Wald statistic equal to

5.834, p= .016; were significantly predictive of the students' *course grade*. Table 16 contains the summary of such model. Additionally, after a close inspection of the odds ratios, we found that (1) an increase in *academic self-discipline* is associated with a probability of approximately 1.1 that the student will perform at a satisfactory level in their mathematics course and (2) an increase in *mathematics and test taking skills* is associated with a probability of approximately 1.05 that the student will perform at a satisfactory level in their mathematics course. On the other hand, our results showed that (1) an increase in *reading and writing skills* was associated with a probability of approximately 0.9 that the student will perform at a satisfactory level in their mathematics course (2) an increase in *test anxiety* was associated with a probability of approximately 0.98 that the student will perform at a satisfactory level in their mathematics course (3) students who are employed reported a probability of approximately 0.43 that they will perform at a satisfactory level in their mathematics course and (4) students who are part-time only reported a probability of approximately 0.6 that they will perform at a satisfactory level in their mathematics course.

CHAPTER VI

CONCLUSIONS AND DISCUSSIONS

The main focus on this study was to investigate the phenomenon of mathematics anxiety on Hispanic college students. Our results from Research Question 1 showed that females had higher significant levels of mathematics anxiety than males. Furthermore, freshman students and non-freshman students seem to share similar levels of mathematics anxiety given that there was not enough evidence to state the contrary. Our data also showed that students enrolled in developmental mathematics courses have higher levels of mathematics anxiety than students enrolled in non-developmental mathematics courses. Students enrolled in developmental mathematics have failed to meet the minimum mathematics requirement set by the university, telling us that those students probably lacked basic math skills throughout their secondary education. Because of that, it is possible that those students might suffer from low self-esteem. These feelings of embarrassment and disappointment could then foster higher levels of mathematics anxiety, as explained by the Inference Model compared to students who are not enrolled in developmental math courses (Liebert & Morris, 1967; Mandler & Saraso, 1952; Wine, 1971). Furthermore, our data showed that students whose major is at the College of Humanities or College of Education have significantly higher levels of mathematics anxiety than those whose major is at the College of Science and Mathematics. An explanation could be that students who already suffer of high levels of mathematics anxiety tend to avoid careers that rely on

mathematical skills, hence why choosing careers in the humanities or education fields (Ashcraft, 2002; Ma, 1999). A comparison was also done when comparing STEM and non-STEM colleges, but the differences, although significant, were not significantly strong. A possible reason for this could be that students from the College of Engineering (which falls under the STEM category) appeared to show high levels of math anxiety.

In response to Research Question 2, our results showed that students who had a full time job had higher levels of mathematics anxiety than those who were not employed. The pressures of having a full-time job in conjunction to going to school could be the explanation for the development of higher mathematics anxiety than those students who do not have a job. On the other hand, being a full-time student or part-time student seems to play no role on the students' mathematics anxiety level given that there was not enough data to state that the math anxiety levels differed among those two groups. Lastly, we wanted to investigate if there existed a family influence on students' mathematics anxiety levels. We did this by investigating whether having at least one grandparent, parent, or sibling who attended college affected the students' math anxiety levels. Data did not show that there existed an influence from a grandparent or sibling, but there was evidence of such influence from part of the parent. Students whose at least one parent attended college reported a significant lower level of mathematics anxiety than those whose parents never attended college. A possible explanation could be that those students whose parents attended college might receive more support from their parents. Being that at least one parent attended college, students might receive more advice as to how to handle college-related stress and anxiety than first generation college students.

Research Question 3 was meant to assess the possible relationship between the study habits of a student and their mathematics anxiety levels. We wanted to know if having good

studying skills yielded lower levels of mathematics anxiety. If such relationship existed, we wanted to see which factors of studying habits were more important. Data showed that from the study habits, an increase in goals and attitude and math skills was associated with a decrease in mathematics anxiety levels. What this says is that the better attitude the student has towards their education as well as stronger math skills, the lower their mathematics anxiety should be. This result tells us that if we want a student to reduce their mathematics anxiety level, we must reinforce how important education is. We must also help them build a stronger foundation in mathematics, hence building a stronger confidence when confronted with a mathematical task and therefore decreasing their anxiety.

For Research Question 4, we wanted to explore the impact that good studying habits and mathematics anxiety could have on students' mathematics performance, measured by their math course grade. Our results showed that increasing the students' math skills and time management skills was associated with an increase in their math course grade. Good time management skills could be crucial for a mathematics course given that in those courses, students are expected to learn multiple mathematical definitions and procedures and it takes time to be able to learn those skills, let alone master. On the other hand, our data showed that an increase in reading skills and a good study environment was associated with a decrease in the students' math course grade. A possible explanation could be that students with higher reading skills are probably students whose majors require a lot of literature-related assignments and not mathematical assignments hence why the negative relationship was found in our results. Also, our model could imply that having a good place to study does not necessarily mean that there will be an increase in the students' math course grade. In fact, the more the student might focus on having a place to study and having everything organized, the less time they could have to actually study, hence

decreasing their math course grade. Lastly, it is important to note that although mathematics anxiety was not considered a statistically significant predictor in our model, there was evidence of a negative relationship between mathematics anxiety and math course grade; a result that has been present throughout the literature (Ma, 1999).

For our last research question, Research Question 5, we wanted to consider all possible factors of a student and the possible impact that those could have on the students' mathematics performance, that is their final exam grade and course grade. Two models were created because of it (multiple regression model and logistic model) rather than exanimating each factor individually using independent sample t-tests or simple linear regressions. Our final exam grade model (multiple regression) showed that an increase in mathematics and test taking skills was associated with an increase in the students' final exam grade. This is not a surprise being that students with better mathematics skills are more likely to score higher on their mathematics assignments and tests. In order for this to happen, mathematics instructors should not only master their field but also have the proper training required to teach the material to students. Another factor that showed a positive relationship was students who were not employed. These nonemployed students were associated with an increase in their final exam scores. It is possible that because they do not have a job, they have more time to study and better prepare for their mathematics courses. Non-employed students could also experience less stress compared with students with either a part-time or full-time job, thus focusing more on their studies. On the other hand, our final exam grade model showed that being in a developmental mathematics course was associated with a decrease in the students' final exam grade. A possible explanation could be that students enrolled in developmental mathematics courses suffer more from mathematics anxiety than students enrolled in non-developmental mathematics courses, thus they are more likely to

score lower on their mathematics final exam grade. Lastly, an increase in reading and writing skills was associated with a decrease in the students' final exam grade. This relationship was confusing at first but a possible explanation was made after exanimating the items that measured the reading and writing skills. After close inspection of such items, it became clear that they measured a more passive style of reading rather than an analytical style required for reading science and mathematics books. This showed us that having "good" reading skills is not enough to perform satisfactory in mathematics courses and it could even hinder the students' mathematics performance. Reading courses should implement a more diverse curriculum that includes assignments that enhance the analytical reading skills of students so that this negative relationship that was seen on our model could be inverted in the future.

Similar findings were encountered in our course grade model (logistic regression). In this model, we found that students who are more disciplined in their academics have a higher probability of passing their mathematics course. This included studying beforehand for upcoming tests and going to see their mathematics professors when they have questions regarding the material covered. An increase in students' mathematics and test taking skills was also associated with a higher probability of passing their mathematics courses. On the other hand, an increase in the students' test anxiety was associated with a lower probability of passing their mathematics courses. This coincides with findings that suggest that anxiety interferes with students' mathematics performance therefore the low probability of passing such courses. Students who were part-time only and employed also reported a lower probability of passing their mathematics courses respectively. This could be because these students probably have a job or other responsibilities outside of school therefore spending less time focusing on their studies. Unfortunately there is not much that can be done in this case but these students should try to

dedicate as much time and dedication to their studies, even if this means making sacrifices. Lastly, an increase in the students' reading and writing skills also showed a lower probability in them passing their mathematics courses. This finding was similar to the one in the final exam model (multiple regression) that suggests that having good passive reading skills is not enough and could even hurt their mathematics performance. Again, reading instructors should emphasize on the importance of analytical reading skills. Mathematics instructors should also implement assignments in their courses that foster such skills.

It is important to also note the factors that were not considered significant by either model. Mathematics anxiety yielded a negative relationship in both models, as shown on numerous studies, yet it was not considered a significant factor. This could had been avoided if the grades that were collected came from instructors who shared similar grading scales, but it is still possible that such insignificance could had still been present. Also, having a family member who has attended college or not seems to play no important role on whether the student will score higher or lower on their final exam and course grade. This tells us that first generation students have the same potential in succeeding in their mathematics courses as students whose family members have had attended college and experienced the demands of such institutions. Lastly, gender, classification, and college of major were not considered significant in our models. This tells us that both males and females, freshman and non-freshman, and STEM and non-STEM majors also have the same potential to succeed in their mathematics courses.

CHAPTER VII

LIMITATIONS AND FUTURE WORK

Despite the careful planning of this study, there still existed some limitations. We were able to receive the students' grades on their final exam and overall course from all instructors who agreed to participate in the study, yet it was clear that they all graded differently. Some instructors gave grades with no decimal points while others graded up to 3 decimal places. Another thing that could have affected the results of this study was that it was not always clear whether the scores received from the instructors were raw, curved, or with extra points added to them by extra credit assignments or corrections. To better enhance a study like this, we would advice to have some control over the grading scheme so that the scores would not differ as much regardless of the instructor but of course this could be an inconvenience to many instructors given that they have probably developed their own grading schemes. Another limitation for this study was the sample size. By increasing our sample size, it could have been possible to gather a better-distributed sample. Examples of this are found in the descriptive statistics of the *college of* major and classification where the sample was not evenly distributed, hence why we had to create new variables to accommodate this issue. By increasing our sample size we could of also have found statistically significant findings on variables in which we were not able to with our current sample size.

For future work, we want to collect more information from the students. This includes more data on their mathematics performance, which would be their ACT and SAT mathematics scores.

We want to investigate the relationship these might have with the students' mathematics anxiety levels. Additionally we would also like to develop our own theoretical model that explains how mathematics anxiety is created. So far we have an idea of what factors contribute to higher levels of math anxiety but with more research done over the factors, we could create a theoretical model that could help us then develop a program to alleviate the symptoms of anxiety and overall reduce mathematics anxiety levels on the students. With a program like this, not only students could benefit from it but anyone whose lives are affected in any way by their mathematics anxiety.

REFEFRENCES

- Abraham, B., & Ledolter, J. (2006). *Introduction to regression modeling*. Thomson Brooks/Cole.
- Aiken, L. R. (1974). Two scales of attitude toward mathematics. *Journal for Research in Mathematics Education*, 67-71.
- Aiken Jr, L. R., & Dreger, R. M. (1961). The effect of attitudes on performance in mathematics. *Journal of Educational Psychology*, *52*(1), 19.
- Armstrong, J. M. (1985). A national assessment of participation and achievement of women in mathematics. *Women and mathematics: Balancing the equation*, 59-94.
- Ashcraft, M. H. (2002). Math anxiety: Personal, educational, and cognitive consequences. *Current Directions in Psychological Science*, 11(5), 181-185.
- Ashcraft, M. H., & Faust, M. W. (1994). Mathematics anxiety and mental arithmetic performance: An exploratory investigation. *Cognition & Emotion*, 8(2), 97-125.
- Ashcraft, M. H., Kirk, E. P. & Hopko, D. (1998). On the cognitive consequences of mathematics anxiety. In C. Donlan (Ed.), *The Development of Mathematical Skills*, (pp. 175-196). Hove, UK: Psychology Press
- Bartlett, M. S. (1935). The effect of non-normality on the *t*-distribution. *Proc. Camb. Phil. Soc.* 31, 223.
- Betz, N. E. (1978). Prevalence, distribution, and correlates of math anxiety in college students. *Journal of counseling psychology*, 25(5), 441.
- Burton, G. M. (1979). Getting comfortable with mathematics. *The Elementary School Journal*, 79, 129-135.
- Brown, R. S., & Niemi, D. N. (2007). Investigating the Alignment of High School and Community College Assessments in California. National Center Report# 07-3. *National Center for Public Policy and Higher Education*.
- Brush, L. R. (1978). A Validation Study of the Mathematics Anxiety Rating Scale (MARS). *Educational and Psychological Measurement*, *38*(2), 485-499.
- Cemen, P. B. (1987). *The nature of mathematics anxiety* (Tech. Rep.). Stillwater: Oklahoma State University. (ERIC Document Reproduction Service No. ED 287 729)

- Chiu, L. H., & Henry, L. L. (1990). Development and validation of the Mathematics Anxiety Scale for Children. *Measurement and evaluation in counseling and development*.
- Culler, R. E., & Holahan, C. J. (1980). Test anxiety and academic performance: The effects of study-related behaviors. *Journal of educational psychology*, 72(1), 16.
- Desiderato, O., & Koskinen, P. (1969). Anxiety, study habits, and academic achievement. *Journal of Counseling Psychology*, 16(2), 162-165.
- Donady, B., & Tobias, S. (1977). Math Anxiety. *Teacher*, 95(3), 71-74.
- Dossel, S. (1993). Maths Anxiety. Australian mathematics teacher, 49(1), 4-8.
- Dreger, R. M., & Aiken Jr, L. R. (1957). The identification of number anxiety in a college population. *Journal of Educational Psychology*, 48(6), 344.
- Dutton, W. H. (1954). Measuring attitudes toward arithmetic. *The Elementary School Journal*, 54, 24-31.
- Dutton, W. H., & Blum, M. P. (1968). The measurement of attitudes toward arithmetic with a Likert-type test. *The Elementary School Journal*, *68*, 259-264.
- Eisenhart, C. (1947). The assumptions underlying the analysis of variance. *Biometrics*, 3(1), 1-21.
- Fennema, E., & Sherman, J. A. (1976). Fennema-Sherman mathematics attitude scale. Instruments designed to measure attitudes toward the learning of mathematics by males and females. *JAS Catalog of Selected Document of Psychology*, 6(31), Ms. No. 1225.
- Fox, L. (2005). Academic achievement of Hispanic students in Orange County public schools: Do Hispanic students have varying degrees of academic success based on the high school they attend? *Dissertation Abstract International*, 66(08), 2883. Doctoral dissertation, University of Central Florida, summer 2005.
- Frary, R. B., & Ling, J. L. (1983). A factor-analytic study of mathematics anxiety. *Educational* and psychological measurement, 43(4), 985-993.
- Gladstone, R., Deal, R., & Drevdahl, J. E. (1960). Attitudes toward mathematics. In M. E. Shaw & J. M. Wright (1967). *Scales for the measurement of attitudes*. NY: Mc Graw Hill. 237-242.
- Gutbezahl, J. (1995). How Negative Expectancies and Attitudes Undermine Females' Math Confidence and Performance: A Review of the Literature. Amherst, MA: University of Massachusetts. (ERIC Document Reproduction Service No. ED 380 279)
- Hadfield, O. D., & McNeil, K. (1994). The relationship between Myers-Briggs personality type and mathematics anxiety among preservice elementary teachers. *Journal of Instructional Psychology*, 21(4), 375-384.

- Hagedorn, L. S., Siadat, M. V., Fogel, S. F., Nora, A., & Pascarella, E. T. (1999). Success in college mathematics: Comparisons between remedial and nonremedial first-year college students. *Research in Higher Education*, *40*(3), 261-284.
- Hebb, D. O. (1955). Drives and the CNS (conceptual nervous system). *Psychological review*, 62(4), 243-254.
- Hembree, R. (1990). The nature, effects, and relief of mathematics anxiety. *Journal for research in mathematics education*, 33-46.
- Hendel, D. D. (1980). Experiential and affective correlates of math anxiety in adult women. *Psychology of Women Quarterly*, 5(2), 219-230.
- Lazarus, M. (1974). Mathophobia: Some Personal Speculations. *National Elementary Principal*, *53*(2), 16-22.
- Levine, G. (1995). Closing the Gender Gap: Focus on Mathematics Anxiety. *Contemporary Education*, 67(1), 42-45.
- Lorenzen, T., & Anderson, V. (Eds.). (1993). *Design of experiments: A no-name approach*. CRC Press.
- Ma, X. (1999). A meta-analysis of the relationship between anxiety toward mathematics and achievement in mathematics. *Journal for research in mathematics education*, *5*, 520-540.
- Mahmood, S., & Khatoon, T. (2011). Development and validation of the mathematics anxiety scale for secondary and senior secondary school students. *British Journal of Arts and Social Sciences*, 2(2).
- Miller, L. D., & Mitchell, C. E. (1994). Mathematics anxiety and alternative methods of evaluation. *Journal of Instructional Psychology*, 21(4), 353-358.
- Mitchell, K. R., & Ng, K. T. (1972). Effects of group counseling and behavior therapy on the academic achievement of test-anxious students. *Journal of Counseling Psychology*, 19(6), 491.
- Pearson, E. S. (1931). The analysis of variance in cases of non-normal variation. *Biometrika*, 114-133.
- Pradeep, R. (2011) A Study of mathematics anxiety among primary pre-service teachers enrolled in a Dutch teacher training program. Unpublished thesis, Universiteit Van Amsterdam.

- Preston, P. A. (1987). Math anxiety: Relationship with sex, college major, mathematics background, mathematics achievement, mathematics performance, mathematics avoidance, self-rating of mathematics ability, and self-rating of mathematics anxiety as measured by the Revised Mathematics Anxiety Rating Scale (RMARS). Unpublished dissertation, University of Tennessee.
- Quilter, D., & Harper, E. (1988). Why we didn't like mathematics, and why we can't do it. *Educational research*, 30(2), 121-134.
- Richardson, F. C., & Suinn, R. M. (1972). The Mathematics Anxiety Rating Scale: Psychometric data. *Journal of counseling Psychology*, 19(6), 551-554.
- Rounds, J. B., & Hendel, D. D. (1980). Measurement and dimensionality of mathematics anxiety. *Journal of Counseling Psychology*, 27, 138-149.
- Sandman, R. S. (1980). The mathematics attitude inventory: Instrument and user's manual. *Journal of Research in Mathematics Education, 11*(2), 148-149
- Suinn, R. M., & Edward, R. (1982). The measurement of mathematics anxiety. The Mathematics Anxiety Rating Scale for Adolescents-MARS-A. *Journal of Clinical Psychology*, *38*(3), 576-580.
- Suinn, R. M., & Winston, E. H. (2003). The mathematics anxiety rating scale, a brief version: psychometric data. *Psychological reports*, *92*(1), 167-173.
- Suinn, R., Taylor, S., & Edward, R. (1988). Suinn Mathematics Anxiety Rating Scale for elementary school students (MARS-E). Psychometric and normative data. *Educational and Psychological Measurement*, 48, 979-986.
- Thompson, G. L., & Joshua-Shearer, M. (2002). In retrospect: What college undergraduates say about their high school education. *The High School Journal*, 1-15.
- Tobias, S. (1985). Test anxiety: Interference, defective skills, and cognitive capacity. *Educational Psychologist*, 20(3), 135-142.
- Tobias, S. (1990). Math anxiety: An update. NACADA journal, 10(1), 47-50.
- Tobias, S., & Weissbrod, C. (1980). Anxiety and mathematics: An update. *Harvard Educational Review*, *50*, 63-70.
- Trujillo, K. M., & Hadfield, O. D. (1999). Tracing the roots of mathematics anxiety through indepth interviews with preservice elementary teachers. *College student journal*, 33(2), 219.
- Warner, R. M. (2008). Applied statistics: From bivariate through multivariate techniques. Sage.

- Wikoff, R. L., Buchalter, B. D. (1986). Factor analysis of four Fennema-Sherman mathematics attitude scales. *International Journal of Mathematical Education in Science and Technology*, 17(6).
- Wittmaier, B. (1972). Test anxiety and study habits. Journal of Educational Research, 352-354.
- Wood, E. F. (1998). Math anxiety and elementary teachers: What does research tell us? *For the Learning of Mathematics*, 8(1), 8-13.

APPENDIX A

APPENDIX A

TABLES

Table 1. Course descriptions

Course Title	Course Description	l							
Elementary Algebra	Topics include basic operations on real numbers, elementary geometry, introduction to algebra, linear equations and graphs, linear equations with applications, exponent properties, systems of linear equations in two unknowns, polynomials and factoring methods.								
Intermediate Algebra	•	Topics include factors of polynomials; rational expressions; radical expressions; an introduction to complex numbers; quadratic equations; rational equations, radical equations and elementary inequalities.							
College Algebra	Topics include nonlinear and absolute value inequalities, functions, complex numbers, polynomial and rational functions, exponential and logarithmic functions, systems of linear and nonlinear equations, and matrices.								
Elementary Statistics	tendency and disper	definitions and fundament sion, empirical and theoret hypotheses, interval estim	ical concepts of probab	bility, the central limit					
Course Title	Course Code	Total Students Enrolled in Course	Total Student Participants in Study	Course Format					
Elementary	1300.01	22	14	Computer Based					
Algebra	1300.01	28	22	Computer Based Computer Based					
(MATH 1300)	1300.02	30	18	Computer Based					
(11111111111111111111111111111111111111	1300.04	30	12	Computer Based					
	1300.05	24	12	Computer Based					
Intermediate	1334.01	28	22	Computer Based					
Algebra	1334.02	30	21	Computer Based					
(MATH 1334)	1334.05	30	25	Computer Based					
	1334.06	29	21	Computer Based					
	1334.07	29	17	Computer Based					

College	1340.05	26	19	Computer Based
Algebra	1340.16	19	14	Computer Based
(MATH 1340)	1340.21	32	24	Lecture Based
	1340.24	32	19	Lecture Based
	1340.26	32	30	Lecture Based
Elementary	2330.05	32	30	Lecture Based
Statistics	2330.07	30	25	Computer Based
(MATH 2330)	2330.16	30	21	Lecture Based
	2330.17	29	25	Lecture Based
	2330.18	23	16	Computer Based

Note: Final exam was common and comprehensive for all courses.

Table 2. List of variables used in the study

Variables	Description	Values
Dependent Variables		
Mathematics Anxiety Score	Numerical score of math anxiety. The higher the score, the more anxious the student.	30~150
Final Exam Grade	Grade obtained by the students on their respective course's final exam	0~100
Course Grade	Overall course grade obtained by the students	0~100
Independent Variables		
Gender	Student gender	1=Male 2=Female
Classification	School classification status	1=Freshman 2=Sophomore 3=Junior 4=Senior
Courses	Course enrollment at time of study	1=MATH 1300 (Elementary Algebra) 2=MATH 1334 (Intermediate Algebra) 3=MATH 1340 (College Algebra) 4=MATH 2330 (Elementary Statistics)
College of major	College that pertains to the major of the student	1=College of Arts and Humanities 2=College of Social and Behavioral Sciences 3=College of Business 4=College of Education 5=College of Science and Mathematics 6=College of Engineering 7=College of Health and Human Services 8=I do not know
School Status	Enrollment status of student	1=Full-Time Student 2=Part-Time Student
Grandparents' education	"At least one of my four grandparents attended or graduated from college"	2=Yes 1=No 0=I do not know
Parents' education	"At least one of my two parents attended or graduated from college"	2=Yes 1=No 0=I do not know
Siblings' education	"I have at least one older brother/sister who attended or graduated college"	1=Yes 0=No

Employment Status	Employment status of the student	1=Full-Time Employee 2=Part-Time Employee 3=Not Employed
Study Habits		
Goals and Attitude	Overall attitude towards education	16~48
Time Mgmt. Skills	Good time-managing skills	6~18
Study Environment	Good studying environment	8~24
Test Taking/Preparation Skills	Good preparation for a test and good test taking skills.	7~21
Note Taking Skills	Good note taking skills	8~24
Reading Skills	Good reading skills	6~18
Math Skills	Good math skills	6~18

Table 3. Mean mathematics anxiety scores by all 9 factors

		N	MA Mean	SD
			50.44	0.4.51
Gender	Male	141	72.41	24.51
	Female	243	86.02	22.73
Classification	Freshman	219	80.03	23.89
	Sophomore	97	83.36	25.10
	Junior	46	79.02	23.69
	Senior	19	84.58	28.07
Courses	MATH 1300 (Elementary Algebra)	63	79.06	23.82
Courses	MATH 1334 (Intermediate Algebra)	104	90.24	23.25
	MATH 1340 (College Algebra)	103	80.26	22.24
	MATH 2330 (Elementary Statistics)	114	74.39	24.93
College of major	College of Arts and Humanities	32	89.56	20.94
Conege of major	College of Social and Behavioral Sciences	71	83.85	26.26
	College of Business	30	78.70	24.89
	College of Education	41	89.32	21.66
	College of Science and Mathematics	61	71.54	24.01
	College of Engineering	25	82.00	24.94
	College of Health and Human Services	117	79.24	23.62
School Status	Full-Time Student	317	80.38	24.43
School Status	Part-Time Student	66	84.61	23.23
Grandparents' education	Yes	49	82.38	24.09
Grandparents education	No	279	81.61	24.90
	I do not know	56	76.89	20.98
Parents' education	Yes	192	78.95	23.97
Parents education	No	184	83.18	24.08
	I do not know	8	81.12	34.34
	I do not know	o	01.12	34.34
Siblings' education	Yes	191	80.42	23.82
C	No	189	81.75	24.97
Employment Status	Full-Time Employee	82	84.49	24.42
-rJ	Part-Time Employee	114	83.35	25.67
	Not Employed	188	78.12	23.09

Note: N = sample size; MA: Mathematics Anxiety Score; SD = standard deviation

Table 4. Comparison of percentile equivalents for Suinn's study and our study of Hispanic students.

Percentage	Suinn's Percentile Equivalents for Students' Mathematics Anxiety Scores	Our Percentile Equivalents for Hispanic Students' Mathematics Anxiety Scores
5%	34	39
10%	37	48
25%	46	66
50%	59	80
75%	78	98
90%	97	112
95%	108	123

Table 5. Summary of ANOVAs for mathematics anxiety mean score differences for variables classification, courses, and college of major.

		Sum of squares	df	Mean square	F	Sig.
Classification	Between groups Within groups Total	1021.281 221978.853 223000.134	2 377 379	510.640 588.803	.867	.421
Courses	Between groups Within groups Total	15180.200 208042.400 223222.601	3 379 382	5060.067 548.925	9.218	.000
College of major	Between groups Within groups Total	12089.445 209994.300 222083.745	6 369 375	2014.907491 569.090243	3.541	.002

Note: df = degrees of freedom; F = F statistic; Sig. = Significance

Table 6. Summary of independent sample t-tests of mathematics anxiety mean score differences for variables gender, classification, courses, college of major, and school status.

	N	Mean	SD	t	Cohen's d
Male	141	72.41	24.51	-5.495***	0.58
Female	243	86.02	22.73		
Freshman	219	80.03	23.89	-0.889	
Non-Freshman	162	82.27	24.99		
Developmental Math	167	86.02	24.02	3.594***	0.37
Non-Developmental Math	217	77.18	23.82		
STEM Colleges	86	74.58	24.60	-2.785**	0.34
Non-STEM Colleges	291	82.86	24.11		
Full-Time Student	317	80.38	24.43	-1.288	
Part-Time Student	66	84.61	23.23		
	Female Freshman Non-Freshman Developmental Math Non-Developmental Math STEM Colleges Non-STEM Colleges Full-Time Student	Male141Female243Freshman219Non-Freshman162Developmental Math167Non-Developmental Math217STEM Colleges86Non-STEM Colleges291Full-Time Student317	Male 141 72.41 Female 243 86.02 Freshman 219 80.03 Non-Freshman 162 82.27 Developmental Math 167 86.02 Non-Developmental Math 217 77.18 STEM Colleges 86 74.58 Non-STEM Colleges 291 82.86 Full-Time Student 317 80.38	Male 141 72.41 24.51 Female 243 86.02 22.73 Freshman 219 80.03 23.89 Non-Freshman 162 82.27 24.99 Developmental Math 167 86.02 24.02 Non-Developmental Math 217 77.18 23.82 STEM Colleges 86 74.58 24.60 Non-STEM Colleges 291 82.86 24.11 Full-Time Student 317 80.38 24.43	Male 141 72.41 24.51 -5.495*** Female 243 86.02 22.73 -0.889 Freshman 219 80.03 23.89 -0.889 Non-Freshman 162 82.27 24.99 Developmental Math 167 86.02 24.02 3.594*** Non-Developmental Math 217 77.18 23.82 STEM Colleges 86 74.58 24.60 -2.785** Non-STEM Colleges 291 82.86 24.11 Full-Time Student 317 80.38 24.43 -1.288

Note: N = sample size; SD = standard deviation *p<.05, **p<.01, ***p<.001.

Table 7. Summary of ANOVAs for mathematics anxiety mean score differences for variable *employment status*.

		Sum of squares	df	Mean square	F	Sig.
Employment Status	Between groups Within groups Total	2923.153 220299.447 223222.601	2 380 382	1461.576576 579.735388	2.521	.082

Note: df = degrees of freedom; F = F statistic; Sig. = Significance

Table 8. Summary of independent sample t-tests of mathematics anxiety mean score differences for variables employment status, grandparents' education, parents' education, and siblings' education.

		N	Mean	SD	t	Cohen's d
F 1	F 1 1	106	02.02	25.10	2.051#	0.22
Employment	Employed	196	83.83	25.10	2.051*	0.22
Status	Non-Employed	187	78.36	22.90		
Grandparent's	Yes	49	82.38	24.09	-0.201	
Education	No	279	81.61	24.90		
Parent's	Yes	192	78.95	23.97	1.708*	0.18
Education	No	184	83.18	24.08		
Sibling's	Yes	191	80.42	23.82	0.530	
Education	No	189	81.75	24.97		

Note: N = sample size; SD = standard deviation *p<.05, **p<.01, ***p<.001.

Table 9. Results of sequential regression for Research Question 3

		Model 1			Model 2			Model 3			Model 4	
Variable	В	SE B	β	В	SE B	β	В	SE B	β	В	SE B	β
Intercept	138.7	10.65	•	138.3	18.46	•	138.6	10.39		139.1	10.38	•
Math Skills	-2.850	.503	318 ***	-2.860	.50	319 ***	-2.833	.488	310 ***	-2.769	.484	309 ***
Goals and Attitude	979	.431	159 *	980	.430	159 *	951	.415	155 *	694	.333	113
Time Mgmt. Skills	.682	.714	.064	.673	.711	.064	.715	.692	.068			
Note Taking Skills	.149	.493	.019	.121	.467	.016						
Reading Skills	910	.499	100									
\mathbb{R}^2		.142			.142			.142			.139	
F for change in R ²		.142			.000			.000			003 ***	

Table 10. Results of sequential regression for Research Question 4

		Model 1			Model 2	
Variable	В	SE B	β	В	SE B	β
Intercept	48.282	6.497		47.010	6.406	
Math Skills	1.860	.405	.274 ***	1.705	.382	.251
Time Mgmt. Skills	2.119	.527	.268	2.011	.519	.254
Reading Skills	902	.401	131	993	.393	145 *
Study Environment	522	.346	106	617	.341	119
Test Taking / Preparation Skills	522	.453	075			
R^2		.123			.120	
F for change in R ²		.123			003 ***	

Note: B = unstandardized regression coefficient; SE B = Standard error of the coefficient; $\beta = \text{standardized coefficient*} p < .05, **p < .01, ***p < .001.$

.

Table 11. List of variables used for Research Question 5 with their corresponding new coding

Variable	Old Coding	New Coding
Gender	1=Males	0=Females
	2=Females	1=Males
Classification	1=Freshman 2=Non-Freshman	0=Freshman 1=Non-Freshman
Course	1= Elementary Algebra 2= Intermediate Algebra 3= College Algebra 4= Elementary Statistics	0=Developmental (Elementary Algebra, Intermediate Algebra) 1=Non-Developmental (College Algebra, Elementary Statistics)
College	1=College of Arts and Humanities 2=College of Social and Behavioral Sciences 3=College of Business 4=College of Education 5=College of Science and Mathematics 6=College of Engineering 7=College of Health and Human Services	0=Non-STEM (College of Arts and Humanities, College of Social and Behavioral Sciences, College of Business, College of Education, College of Health and Human Services) 1=STEM (College of Science and Mathematics, College of Engineering)
Grandparents' Education	0=I do not know 1=No 2=Yes	0=No 1=Yes
Parents'	0=I do not know	0=No
Education	1=No 2=Yes	1=Yes
Siblings' Education	0=I do not know 1=No 2=Yes	0=No 1=Yes
Employment Status School Status	1=Full-Time 2=Part-Time 3=No Employment 1=Full-Time	0=Employed 1=No Employment 0=Part-Time
	2=Part-Time	1=Full-Time

Table 12. Rotated component matrix of the factorial analysis for study habits items

Items	Factor 1	Factor 2	Factor 3
	(Academic Self-Discipline)	(Reading and Writing Skills)	(Mathematics and Test Taking Skills)
SHQ18	.654	.251	.020
SHQ17	.633	.090	.089
SHQ7	.583	.134	.053
SHQ22	.583	.333	.148
SHQ8	.582	068	.144
SHQ30	.517	.333	.058
SHQ19	.516	028	.280
SHQ3	.494	.167	.205
SHQ14	.467	.038	.337
SHQ4	.457	.114	.215
SHQ43	.450	.381	.091
SHQ31	.446	.359	.117
SHQ21	.445	.163	.283
SHQ5	.442	.092	.222
SHQ9	.441	025	.015
SHQ11	.429	.249	.078
SHQ23	.411	.288	.041
SHQ24	.366	.327	.029
SHQ20	.352	055	.258
SHQ13	.349	.156	.321
SHQ29	.345	.263	013
SHQ45	.340	.302	.214
SHQ6	.324	.048	.051
SHQ28	.323	.226	.138
SHQ2	.314	.115	.014
SHQ10	.313	.031	.024
SHQ1	.245	.161	.166
SHQ38	.235	.224	.115
SHQ33	.220	.177	.159
SHQ51	.156	.590	.067
SHQ50	.076	.586	.059
SHQ47	.179	.561	016
SHQ48	086	.560	.077
SHQ46	022	.559	.142
SHQ42	.195	.529	.341
SHQ44	.158	.522	.304
SHQ41	.299	.516	.048
SHQ49	.090	.474	004
SHQ40	.294	.470	.329
SHQ27	.313	.385	.210
SHQ26	.273	.379	.151
SHQ25	.343	.366	.110
SHQ37	.184	.301	.235

SHQ56	.022	.131	.732
SHQ57	.022	.208	.674
SHQ52	.124	.104	.628
SHQ39	.180	.253	.561
SHQ16	036	095	.530
SHQ34	.195	.302	.522
SHQ12	.198	.082	.512
SHQ53	.277	.059	.484
SHQ35	019	.437	.459
SHQ54	.302	.071	.450
SHQ36	013	.288	.434
SHQ15	225	.051	420
SHQ55	.049	.053	.309
SHQ32	.159	.139	.182

Note: SHQ: Study Habits Question. Extraction Method: Principal Component Analysis. Rotation Method: Quartimax.

Table 13. Rotated component matrix of the factorial analysis for mathematics anxiety items

Items	Factor 1 (Mathematics Test Anxiety)	Factor 2 (Numerical Anxiety)
MAQ4	.857	.050
MAQ3	.854	.067
MAQ12	.812	.245
MAQ5	.808	.048
MAQ1	.794	.136
MAQ9	.787	.122
MAQ2	.753	.151
MAQ8	.721	.167
MAQ11	.709	.312
MAQ14	.691	.261
MAQ10	.679	.270
MAQ7	.676	.121
MAQ15	.637	.360
MAQ6	.596	.216
MAQ13	.518	.382
MAQ29	.123	.820
MAQ30	.172	.796
MAQ21	.170	.785
MAQ17	.071	.782
MAQ28	.302	.750
MAQ18	021	.745
MAQ27	.108	.745
MAQ19	.180	.736
MAQ23	.198	.724
MAQ20	.165	.720
MAQ26	.213	.683
MAQ25	.239	.636
MAQ24	.251	.633
MAQ16	.407	.561
MAQ22	.466	.537

Note: MAQ: Mathematics Anxiety Question. Extraction Method: Principal Component Analysis. Rotation Method: Quartimax.

Table 14. Summary of independent sample t-tests of final exam grade differences for binary variables gender, classification, courses, college of major, grandparents' education, parents' education, siblings' education, school status, and employment status.

		N	Mean	SD	t	Cohen's d
Gender	Male Female	223 129	61.47 57.80	22.38 23.52	-1.453	
Classification	Freshman Non-Freshman	204 145	63.87 55.17	22.26 22.50	3.584***	0.39
Courses	Developmental Math Non-Developmental Math	158 194	70.54 51.64	21.12 20.61	8.458***	0.88
College of major	STEM Colleges Non-STEM Colleges	88 256	58.85 60.68	22.47 23.00	.647	
Grandparent's Education	No Yes	250 47	57.89 63.23	22.63 21.28	-1.500	
Parents' education	No Yes	163 180	60.98 59.02	23.30 22.60	.793	
Siblings' education	No Yes	174 173	59.39 60.61	22.50 60.61	501	
School Status	Part-Time Student Full-Time Student	57 294	53.16 61.57	24.43 22.29	-2.565*	0.36
Employment Status	Employed Not Employed	174 178	56.77 63.40	23.11 22.15	-2.748**	0.29

Note: N = sample size; SD = standard deviation

^{*}p<.05, **p<.01, ***p<.001.

Table 15. Results of sequential regression for Research Question 5

		Model 1			Model 2			Model 3			Model 4			Model 5	
Variable	В	$S \to B$	β	В	SEB	β	В	$S \to B$	β	В	SEB	β	В	SEB	β
Intercept	44.521	11.239		44.525	11.220		40.415	9.962		42.820	9.747		52.264	7.730	
Courses	-21.389	2.524	471 ***	-21.355	2.337	470 ***	-21.072	2.309	464 ***	-21.209	2.307	467	-21.145	2.312	466
Mathematics and Test Taking Skills	1.040	.327	.202	1.040	.326	.202	1.086	.321	.211	1.105	.320		1.199	.316	.233
Reading and Writing Skills	809	.303	* *	810	.302	**	799	.301	**	787	.301	**	531	.255	126
Employment Status	4.496	2.314	.100	4.488	2.299	660.	4.600	2.293	.102	5.128	2.248	* *	5.131	2.254	* *
Academic Self- Discipline	.293	.186	.108	.294	.183	.108	.296	.183	.109	.290	.183	.106			
School Status	3.736	3.241	090	3.710	3.153	090	3.638	3.150	.058						
Numerical Anxiety	073	.092	042	073	.092	042									
Classification	.092	2.586	.002												
\mathbb{R}^2		.254			.254			.253			.250			.244	
F for change in \mathbb{R}^2		.254			* * 000			***			003			900:-	

Note: B = unstandardized regression coefficient; SE B = Standard error of the coefficient; $\beta = \text{standardized coefficient}$ *p < .05, **p < .01, ***p < .001.

Table 16. Logistic regression model for Research Question 5

Variables	В	SE	Wald	Odds	95% CI for	Odds Ratio
				Ratio	Lower	Upper
Academic Self- Discipline	.090	.026	11.812	1.094**	1.040	1.152
Reading and Writing Skills	137	.042	10.366	.872**	.803	.948
Employment Status (Ref: Non-Employed)	830	.344	5.834	.436*	.222	.855
School Status (Ref: Full-Time Student)	540	.379	2.028	.583	.277	1.225
Mathematics and Test Taking Skills	.047	.046	1.051	1.048	.958	1.147
Test Anxiety	014	.012	1.234	.986	.963	1.011
Intercept	-1.725	1.657				

NOTE. *p < .05, B=unstandardized regression coefficient; SE = Standard error of the coefficient; CI = Confidence Interval

APPENDIX B

APPENDIX B

FIGURES

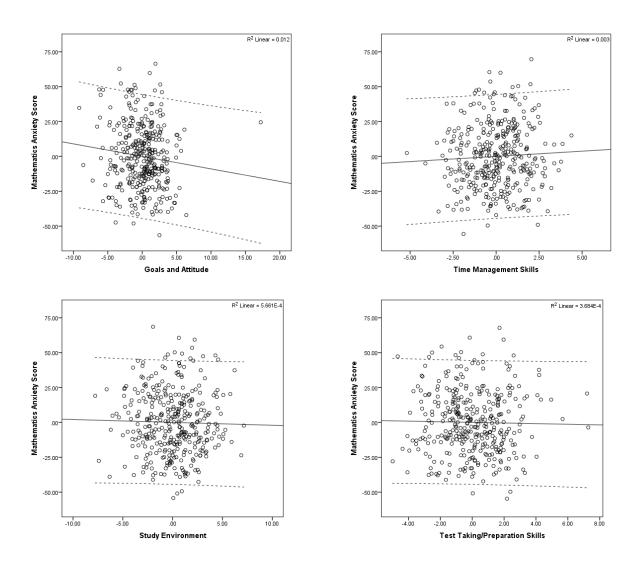


Figure 3. Partial regression plots for all pairs of variables 95% confidence intervals.

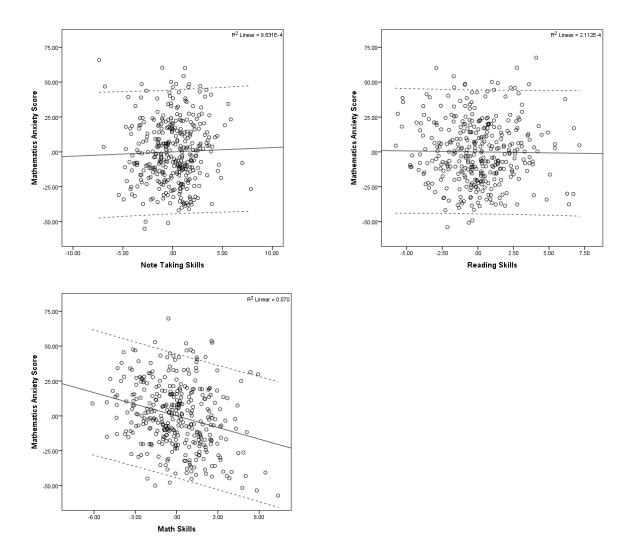


Figure 3. (Continued) Partial regression plots for all pairs of variables 95% confidence intervals.

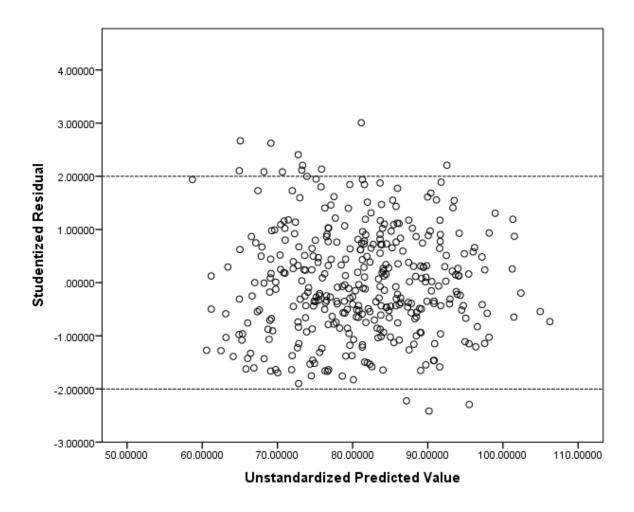


Figure 4. Scatterplot of studentized residuals against unstandardized predicted values within two standard deviations away from the mean.

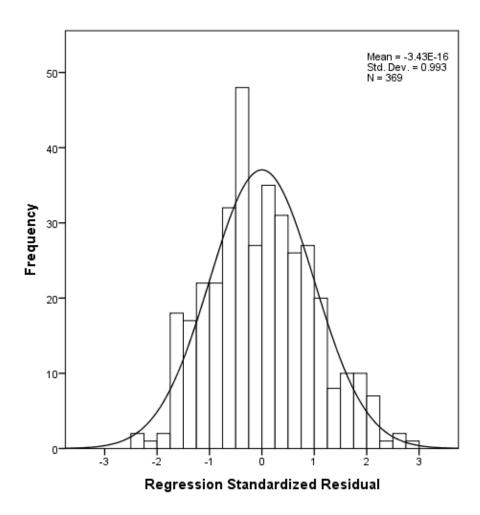


Figure 5. Histogram for normality of standerized residuals.

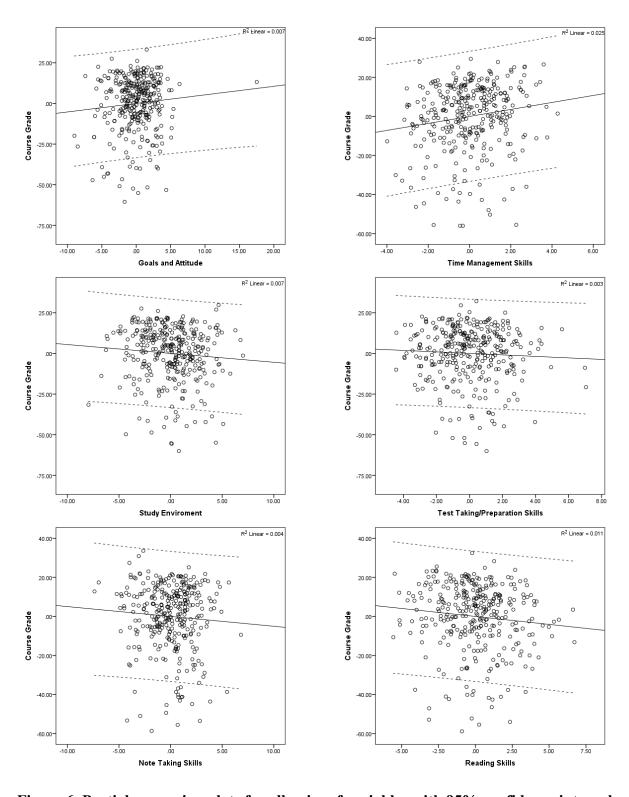


Figure 6. Partial regression plots for all pairs of variables with 95% confidence intervals.

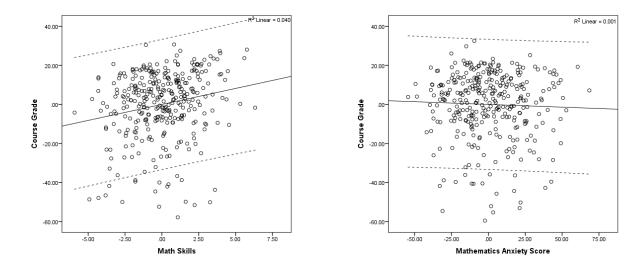


Figure 6. (Continued) Partial regression plots for all pairs of variables with 95% confidence intervals.

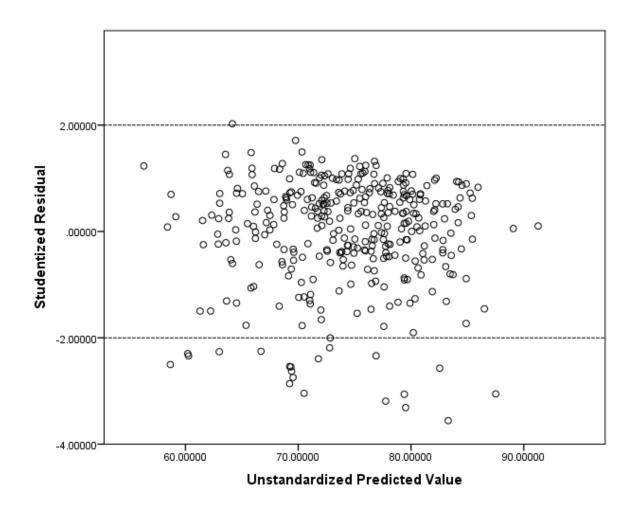


Figure 7. Scatterplot of studentized residuals against unstandardized predicted values within two standard deviations away from the mean.

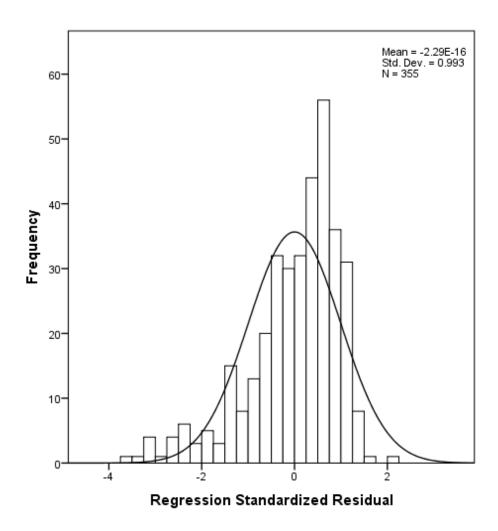


Figure 8. Histogram for normality of standardized residuals.

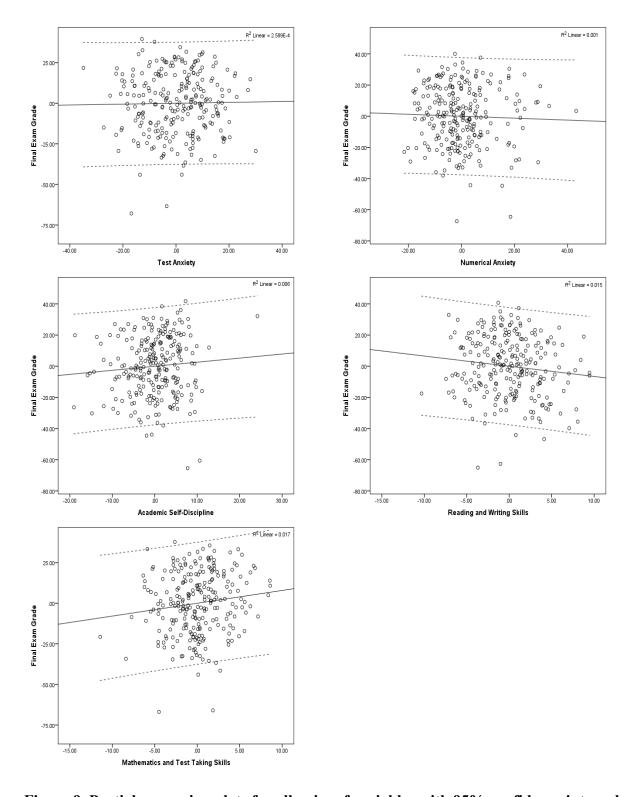


Figure 9. Partial regression plots for all pairs of variables with 95% confidence intervals.

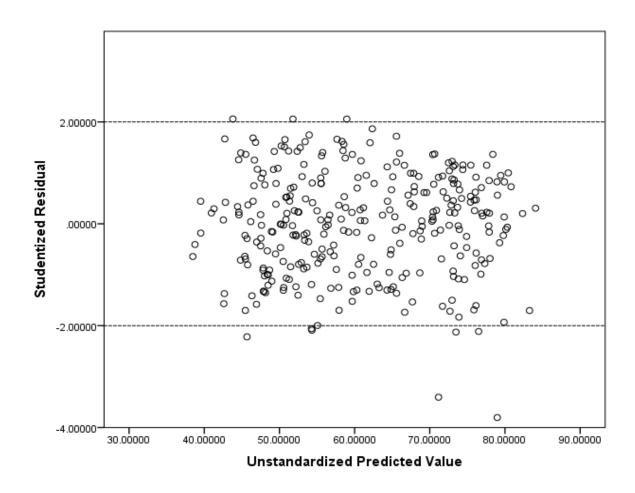


Figure 10. Scatterplot of studentized residuals against unstandardized predicted values within two standard deviations away from the mean.

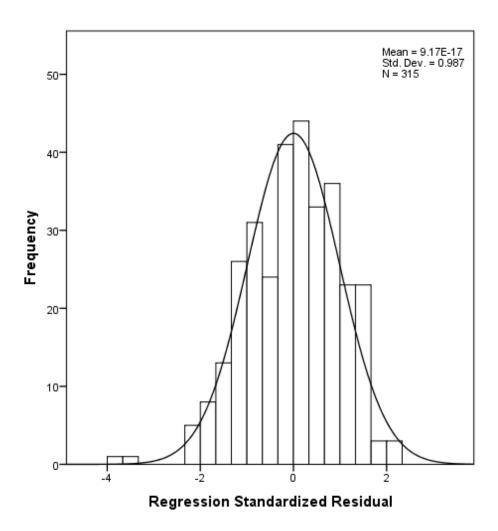


Figure 11. Histogram for normality of standardized residuals.

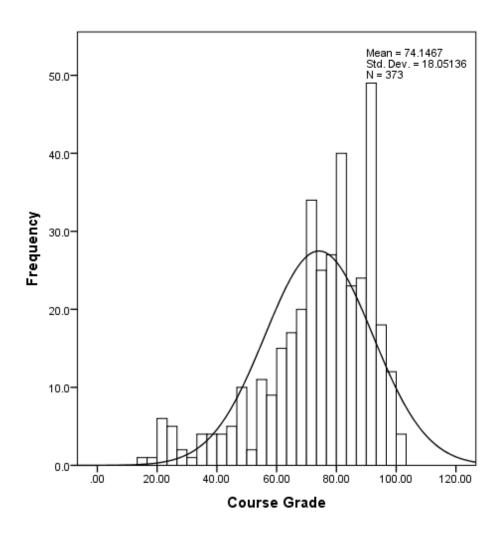


Figure 12. Histogram showing non-normality of variable *course grade*

APPENDIX C

APPENDIX C

FORMS

Student Participation Consent Form

<u>The University of Texas – Pan American</u> Informed Consent Document (Students over the age of 18)



Study title: A Study on Hispanic College Students' Mathematics Anxiety, Study Habits and Academic Performances on Mathematics

This research is being conducted by Dr. Xiaohui Wang and Luis Fernandez from the University of Texas - Pan American. The purpose of this study is to investigate which groups of Hispanic college students (overall, or by major, classification, and sex) seem to suffer higher levels of mathematics anxiety and compared determining factors (education levels of family members, school status, work status). Further, we will study the relationship among the mathematics anxiety, students study habits and their academic performance. If you are not 18 years or older, please do not complete the survey.

In this research study, we will ask you to complete a survey on your feelings about studying mathematics, and your study habits. The surveys will be administered at the beginning of the course and it can be completed in a single 15-20 minute session. We ask that you try to answer all questions. However, if there are any questions that you would prefer to skip, simply leave the answer blank. Your responses on the survey will be kept confidential. You should not write any identifying information on a survey. All surveys will be kept securely stored and will not be viewed by anyone other than the researchers involved in the project.

Your participation in this research study will last throughout the semester you are enrolled in one of the participating courses or programs. You may withdraw from this study at any time without penalty or adverse effects on your course grades, and without being denied benefits to which you are otherwise be entitled.

There are no anticipated risks associated with participation in this study. There will be no direct benefits to participants who take part in it. However, your participation will provide important information about study the relationship among the mathematics anxiety, students study habits and their academic performance and therefore benefit future students.

As part of this research study, your mathematics background scores (math scores from ACT, THEA, SAT or TASK; or Math 1300 or Math 1334 grades if they took the courses at UTPA), final exam grades and attendance in this current course will be used as supporting quantitative data to evaluate the relationship among the mathematics anxiety, students study habits and their academic performance. Your graded coursework will be used anonymously in the research study. The Family Education Rights and Privacy Act of 1974 provides privacy protection of a student's academic record and limits the release of such records without the student's consent. All records will be kept securely stored and will not be viewed by anyone other than the researchers involved in the project. Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission.

For questions about the research itself or to report any adverse effects during or following participation, contact the researcher, Dr. Xiaohui Wang, at (956) 665-3454 or xhwang@utpa.edu at the University of Texas—Pan American, Statistical Consulting Center.

r our organitate minerale, me	a you have read the information provided above at	na have decided to participate.
Signature	Print Full Name	Date
	ewed by the Institutional Review Board for the	
	our rights as a participant, or if you feel that your	

nature indicates that you have read the information provided above and have decided to neuticipate

IRB at 956-665-2889 or irb@utpa.edu. You may also provide anonymous feedback to the IRB by visiting www.utpa.edu/IRBfeedback.

Please keep a copy of this sheet for your reference.

Part A. General Information

	cipant ID:	_						
Date:								
Part 1	l: Background Informa	ition						
1.	What is your gender	? Please :	select ONLY	ONE of the fo	llowin	ıg.		
	M	ale			Fema	le		
2	Please list your curre	ont ago						
۷.	r lease list your curre	entage		_				
3.	What is your classific	cation? Pl	ease select	ONLY ONE of	the fol	lowing.		
	Freshman	Soph	omore	Junior			Senior	
4.	In what college is you	ur major c	offered at? P l	lease select O	NLY O	NE of the	e following.	
	College of Arts and Social and Humanities Behaviora Sciences	Busine			Eng	ollege of gineering	College of Health and Human Services	I do not know
5.	Please select one of t	he followi	ng regarding	g your student	status.	Please	select ONL	Y ONE of
	I am a FULL-TI I am enrolled in 12						student; that	
	ram emoned m <u>12</u>		mege nours.	Talli ei	nonea	in iess uia	<u>an 12</u> college	nours.
6.	Please select one of t the following.	he followi	ng regarding	g your work sta	atus. Pl	ease sel	ect ONLY O	NE of
	I have a FULL-TIME jo I am employed and wo 30~40 hours per v	rk about	I am employ	RT-TIME job; tha yed and work al hours per week.	oout	Ian	not emplo	yed.

	Yes	No	I do not know.					
8.	At least one of my parents atte the following.	nded or graduated from college.	Please select ONLY ONE of					
	Yes	No	I do not know.					
9.	I am the oldest child in my fam	ily. Please select ONLY ONE of	the following.					
	Yes No I do not know.							
	9.1 If you answered "NO" t brother/sister who at following.	o 9, please answer the following tended or graduated college. Pl o	: I have at least one older ease select ONLY ONE of the					
	brother/sister who at	o 9, please answer the following tended or graduated college. Ple	g: I have at least one older ease select ONLY ONE of the					

Part B. Study Habits

Study Habit Questionnaire

Please select only one option per statement.

Go	als and Attitude	Not True	Sometimes True	Always True
1.	I get enough sleep at night so I am attentive during school.		1140	
2.	I believe I am responsible for how I do in school.			
3.	I have a positive attitude towards school and learning			
4.	I have established goals concerning school.			
5.	I know exactly what I have to do to achieve those goals.			
6.	I am working to fulfill those goals.			
7.	I try my best in school each day.			
8.	I do my homework.			
9.	I have the things I need for class.			
10.	I get along well with my teachers.			
11.	I take good notes in class.			
12.	I am good at taking tests.			
13.	I ask and answer questions in class.			
14.	I am happy with my grades.			
15.	Because I don't like math, I spend little time working on my math course			
16.	Because I am good at math, I usually spend less time working on my math course (homework, studying, etc.)			

Time Management	Not True	Sometimes True	Always True
17. I have prioritized my activities so schoolwork comes first.			
18. I schedule time each day to study.			
19. I hand all assignments, papers, and projects on time.			
20. I attend school regularly.			

	Not True	Sometimes True	Always True
21. I keep up and don't get behind.			
22. I use my time effectively when I study.			

Study Environment		Sometimes True	Always True
I regularly study at the same time.			
I have an area in which I can go and study.			
My study area is free of noise and distractions.			
My area of study is very comfortable.			
by the state of th			
My friends leave me alone when I am studying.			
I use time between my classes to study.			
I study for each class every day			
	I regularly study at the same time. I have an area in which I can go and study. My study area is free of noise and distractions. My area of study is very comfortable. I can study for at least 30 minutes without getting up, walking about, taking a snack, or TV or phone breaks. My friends leave me alone when I am studying. I use time between my classes to study.	I regularly study at the same time. I have an area in which I can go and study. My study area is free of noise and distractions. My area of study is very comfortable. I can study for at least 30 minutes without getting up, walking about, taking a snack, or TV or phone breaks. My friends leave me alone when I am studying. I use time between my classes to study.	I regularly study at the same time. I have an area in which I can go and study. My study area is free of noise and distractions. My area of study is very comfortable. I can study for at least 30 minutes without getting up, walking about, taking a snack, or TV or phone breaks. My friends leave me alone when I am studying. I use time between my classes to study.

Te	Test Taking/Preparation Skills		Sometimes True	Always True
31.	I start reviewing for major exams at least 3 days in advance			
32.	I belong to a study group			
33.	I attend extra help sessions or office hours provided by the instructor			
34.	I know what kind of tests I will take, i.e., essay, multiple choice, and how to prepare for different types of tests			
35.	I can predict what types of questions will be on the test			
36.	I am able to finish my tests in the allowed period of time			
37.	If I do not do well on a test, I review it with the instructor and/or analyze it to see where I had problems			

Note Taking Skills	Not	Sometimes	Always
	True	True	True
38. I usually take notes for math courses			

		Not True	Sometimes True	Always True
39.	I am able to take notes in class, keep up with the instructor, and understand the concepts at the same time			
40.	I have an efficient system of taking notes			
41.	I review my notes after each class, preferably right after class			
42.	I know what is the "important stuff" to write down			
43.	In addition to highlighting, I make notes as I read class materials			
44.	I can put class notes or notes from texts into my own words			
45.	I use my notes when I study for homework and exams			

Reading Skills		Not True	Sometimes True	Always True
46.	I can read and learn at the rate of 12-15 pages per hour for history-type material			
47.	I keep up with the readings for all my classes and have the material read before the lecture			
48.	I can concentrate and understand the material I read without re- reading a second or third time			
49.	When reading a text, I read the headings and chapter outlines first			
50.	I adjust my reading styles when I am reading for literature, social science, or science classes			
51.	\boldsymbol{I} do my study-reading during the time of day when \boldsymbol{I} am most alert			

Ma	Math Skills		Sometimes True	Always True
52.	I have a good command of the prerequisite skills for the math class in which I am enrolled			
53.	I always do my homework assignments and work the problems before looking at the solutions			
54.	I participate in class discussions and ask questions when I don't understand a concept			
55.	I at most miss only two math classes per semester			
56.	I can explain to another student how to solve all the problems on a math test			
57.	I have enough time after taking my tests to review for calculation errors and "stupid" mistakes like misplaced + or – signs			

Part C. MARS-B

NAME	Total So	core			
MATHEMATICS ANXIETY RATING S	CALE:	SHOR	r vers	ION	
The items in the questionnaire refer to things that may caplace a check in the box under the column that describes days. Work quickly but be sure to consider each item indi	how much	r appreh you are	nension. I e frighten	or each ed by it	item, nowa-
	Not at	A little	A fair amoun	t Much	Very
1. 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.		0		0	0
5. Thinking about an upcoming math test five minutes before.	0		0	0	
 Waiting to get a math test returned in which you expected to do well. 	0 .			0	
7. Receiving your final math grade in the mail.					0
Realizing that you have to take a certain number of math classes to fulfill the requirements in your major.	0				
9. Being given a "pop" quiz in a math class.			0		0
10. Studying for a math test.			0	0	
11. Taking the math section of a college entrance exam.			0		
12. Taking an examination (quiz) in a math course.		0			
 Picking up the math text book to begin working on a homework assignment. 			0		
 Being given a homework assignment of many difficult problems which is due the next class meeting. 					
15. Getting ready to study for a math test.					

Copyright@ 2004 by Richard M. Suinn. All rights reserved

		Not at	A little	A fair amount	Much	Very much
16.	Dividing a five digit number by a two digit number in private with pencil and paper.	0				
17.	Adding up 976 + 777 on paper.	0		0		0
18.	Reading a cash register receipt after your purchase.	- 0	0		0	
19.	Figuring the sales tax on a purchase that costs more than \$1.00.	0	0	0	0	0
20.	Figuring out your monthly budget.				0	0
21.	Being given a set of numerical problems involving addition to solve on paper.	0		0	0	0
22.	Having someone watch you as you total up a column of figures.	0				
23.	Totaling up a dinner bill that you think overcharged you.					
24.	Being responsible for collecting dues for an organization and keeping track of the amount.	0				
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.	0	0	0	0	
26.	Totaling up the dues received and the expenses of a club you belong to.			0	0	0
27.	Watching someone work with a calculator.		0		0	
28.	Being given a set of division problems to solve.	0		0	0	0
29.	Being given a set of subtraction problems to solve.		0		0	0
30.	Being given a set of multiplication problems to solve.		0	0		0
-			The same of the sa		****	

BIOGRAPHICAL SKETCH

Luis Miguel Fernandez was born in Hidalgo, Texas on April 22, 1992. He graduated from Pharr-San Juan-Alamo high school in 2010 and from the University of Texas Pan-American (UTPA) in 2013 with a Bachelor of Science in Applied Mathematics with a minor in Spanish.

During his undergraduate education, he was president of his university's chapter for the Society for the Advancement of Chicanos and Native Americans in Science (SACNAS). During his presidency, the SACNAS chapter organized events that brought awareness of the STEM field to the community, especially children. One example is the nationally recognized Hispanic Engineering Science and Technology (HESTEC) week held yearly at UTPA. During 2013's HESTEC, the SACNAS chapter managed to create a maglev train with the use of small magnets and they used their demonstration to explain the mechanics of it to young children. During his presidency, the SACNAS chapter also managed to fund 6 students for SACNAS's national conference held in San Antonio, Texas in 2013. The presidency was then passed to Martin Corona who will end his presidency in fall 2015.

Luis received a Master of Science in Mathematical Sciences from UTPA in July 2015. He plans to pursue a doctorate degree in STEM Education at the University of Texas at Austin in Austin, Texas. With this degree, he plans to inspire future mathematics teachers into becoming mentors to their future students. He also aims to mentor his own students into going to national conferences, doing research with faculty, and pursuing a graduate degree. His current mailing address is 305 East Dicker Drive, Pharr Texas, 78577.