The association of statistics anxiety, attitude toward statistics and mathematics self-concept with performance in a business statistics course

Moletenyane Mokhele

Faculty of Agricultural and Natural Sciences,

University of the Free State

Department of Mathematical Statistics and Actuarial Science

Promoter

Dr. Linda van der Merwe

Co-Promoter

Dr. Michael J von Maltitz

June 2018

Submitted in fulfilment of the requirements in respect of the Master's Degree qualification in Statistics in the Department of Mathematical Statistics and Actuarial Science in the Faculty of Agricultural and Natural Sciences at the University of the Free State.

Declaration

I, Moletenyane Mokhele, hereby declare that this work, submitted for the Master's Degree qualification in Statistics at the University of the Free State, is my own original work and has not previously been submitted, for degree purpose or otherwise, to any other institution of higher learning. I further declare that all sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references. Copyright hereby cedes to the University of the Free State.

Signature:.. *Date:*......18 September 2018..

Dedication

To my parents, ***Mac-Millan Clarke Konote (RIP) and Mamolete Konote.***

I have never taken any compliments to heart because deep down inside I know that all of them actually belong to you both, I have no words to acknowledge the sacrifices you made and the dreams you had to let go, just to give me a shot at achieving mine.

Thank you, for everything.

Acknowledgements

I have been extremely fortunate for all the support I have received for the entire journey of this dissertation to its full completion. First and foremost I would like to thank the Lord, Almighty God for His guidance, day and night and His grace I witness. I want to thank the University of the Free State, particularly the Department of Mathematical Statistics and Actuarial Science.

I owe a great debt of gratitude to Dr. Linda van der Merwe, for her guidance throughout my postgraduate student life, for believing that I could do things for which I deemed impossible, for inspiring and pushing me to new levels and for her much appreciated mentorship. A special thanks to Dr. Michael J. von Maltitz, for his suggestions and constant reviews, thank you so much Dr., you unleashed my full potential.

The financial assistance of the National Research Foundation (NRF) towards this research is hereby acknowledge. Opinions expressed and conclusions arrived at are those of the author and not necessarily to be attributed to the NRF or UFS. I want to thank my family: my father, mother, brother and sisters for the spirit they always instilled in me. I cannot afford to forget to thank Lydia Nosipho Khang, for her constant love and support. Despite the abstraction of my study, I could always run my ideas to her. I also want to thank Mr. Gaonyalelwe Maribe, for introducing me to his precept of research, introducing me to Latex and R. A special vote of thanks goes to all students in the first year business statistics course, for providing the data which was used in this project.

Contents

List of Tables

List of Figures

Abstract

Statistics anxiety is a pervasive problem in many fields of study. A large proportion of students identify statistics courses as the most anxiety-inducing courses in their curriculum. It is important to investigate students' anxiety as it can negatively affect students' performance and their overall psychological and physiological condition. Furthermore, understanding about a student's level of anxiety may help teachers find ways to reduce the level of anxiety and enhance the learning experienced by students.

This empirical study examined the relationship between statistics anxiety, attitude toward statistics, and mathematics self-concept as well as their effect on performance in an introductory business statistics course with 103 students (50 males and 53 females). In addition, the study aimed to determine whether statistics anxiety differs by gender and to investigate the experiences and opinions of students regarding statistics anxiety by means of interviews. Statistics anxiety and attitude toward statistics was measured using the Statistics Anxiety Rating Scale (STARS). Ten questions were added to the STARS to measure mathematics self-concept. Performance measures included two tests and final examination marks. Face-to-face, semi-structured interviews were conducted after the examination was written.

Keywords: Statistics Anxiety, attitude toward statistics, mathematics self-concept, academic performance, gender differences

Acronyms

ANOVA	Analysis of Variance
ATS	Attitude toward Statistics
Coeff	Coefficient
MANOVA	Multivariate Analysis of Variance
MD	Mean Difference
Q-Q plot	Quantile-Quantile plot
SAM	Statistics Anxiety Measure
SAS	Statistics Anxiety Scale
SAS Software	Statistical Analysis System software
SD	Standard deviation
S.E	Standard Error
SEM	Standard Error of Measurement
SELS	Self-Efficacy to Learn Statistics
SPSS	Statistics Package for the Social Sciences
STARS	Statistics Anxiety Rating Scale
UFS	University of the Free State
VIF	Variance Inflation Factor

Chapter 1

Orientation to the Study

1.1 Introduction

The concept of statistics anxiety has received increasing attention over the past number of years in the field of statistics education. According to Hawkey (1995), the advent of the computer age and the widening array of vocations that require a theoretical and practical knowledge of statistics and mathematics have all contributed to the emphasis on statistics achievements. Accordingly, students from a broad spectrum of disciplines enrol statistics modules in higher education. There is general agreement that statistics is an important subject in a modern world and that the appearance of statistics anxiety is as likely to cause inadequacy as any real lack of statistical ability (Williams, 2010). Anxiety, fears, worries and self defeating attitudes of statistics have been identified by different researchers and ample evidence has been presented that emotions as well as intellect play a major role in statistics education.

Statistics anxiety is a problem for many students, with the majority experiencing it to some degree and many avoiding statistics courses until late in their different degree disciplines (Onwuegbuzie and Wilson, 2003; Onwuegbuzie, 2004; Williams, 2010). Statistics has always been an anxiety provoking major for most students and with that, most students choose non-mathematical subjects with an intention to avoid calculations or majors with mathematical principles. However, many students have to face statistics as a subject as they progress in their majors. Of these, it was found that about 80% of social and behavioural sciences students experience statistics anxiety (Onwuegbuzie and Wilson, 2003).

According to Blalock Jr (1987), statistics anxiety can affect students' performance in statistics classes, and cause feelings of inadequacy and low self-efficacy for statistics related activities. Furthermore, some researchers (Webb, 1972; Fitzgerald et al., 1996) have reported that statistics anxiety negatively influences students' achievements in statistics courses. Moreover, other researchers (Roberts and Bilderback, 1980; Onwuegbuzie et al., 1997) have found that statistics anxiety often leads students to delay enrolling in statistics courses, thereby affecting the attainment of their degrees.

Statistics anxiety is one of the main independent variables in this study. Researchers have documented a large amount of information on statistics anxiety over the years. For instance, there are multiple definitions of statistics anxiety available. Onwuegbuzie et al. (1997, p. 28) defined statistics anxiety as "a state-anxiety reaction to any situation in which a student is confronted with statistics in any form and any time". Cruise et al. (1985, p. 92) defined statistics anxiety as "the feeling of anxiety encountered when taking a statistics course or doing statistical analysis: that is, gathering, processing and interpret[ing]". Some articles and research studies toward statistics anxiety summarise statistics anxiety as "attitude of students toward statistics which is characterised by worry". In addition, Zeidner (1991, p. 319) defined statistics anxiety as, "a particular form of performance anxiety characterised by extension worry, intrusive thoughts, mental disorganisation, tensions, and physiological arousal". Borkovec et al. (1983) defined worry as a series of unhealthy thoughts that negatively permeate one's mind and can be "relatively uncontrollable". Worry and emotionality are akin to test anxiety (Sarason, 1980). According to Hembree (1988), students with statistics anxiety experience increased cognitive interference when learning and are subject to more encoding difficulty. Moreover, both these psychological concepts (worry and emotionality) directly interfere with student performance contingent on students' coping skills.

Attitude toward statistics and statistics anxiety have been found to be highly correlated with attitude toward statistics often influencing statistics anxiety (Zeidner, 1991; Mji and Onwuegbuzie, 2004). Students with negative experience from mathematical or statistical courses or instructors are often scared and carry such memories in the form of anxiety. Students with negative attitude toward statistics are thought to be highly anxious with regard to statistics (Mji and Onwuegbuzie, 2004). Chew and Dillon (2014) provided more evidence when they stated that attitude toward statistics is defined as an individual's disposition to respond either favourable or unfavourable to statistics or learning statistics.

Onwuegbuzie and Wilson (2003) stated that statistics anxiety is often been associated with mathematics self-concept, indicating that most students with poor mathematical background or self-concept tend to have high levels of anxiety. Bandura (1986) defines self-concept as a view of the self that is developed through experiences. Therefore, experiences with mathematics will form the mathematics self-concept, as well as other attitudinal aspects, through evaluations of those experiences in terms of success or failure (Bandura, 1986; Williams, 2014). Erdogan and Sengul (2014) define mathematics self-concept as self-perception created with the effects of past mathematics experiences and social environment. Most of the studies support the belief that self-concept is a strong facilitator of academic achievement in mathematics and that a positive or negative change in self-concept tends to produce a commensurate change in students' performance (Bandura, 1986; Erdogan and Sengul, 2014; Williams, 2014).

Mathematics anxiety is another anxiety which has been related to statistics anxiety (Onwuegbuzie et al., 1997). However, most researchers consider both anxieties as two separate entities (Cruise et al., 1985; Zeidner, 1991; Onwuegbuzie et al., 1997). According to Richardson and Suinn (1972, p. 551), "mathematics anxiety involves feelings of tension and anxiety that interfere with the manipulation of numbers and solving of mathematical problems in a wide variety of ordinary life and academic situations". Initially, mathematics anxiety was conceptualised as a unidimensional construct (Richardson and Suinn, 1972). When mathematics anxiety was first identified, researchers conceived the construct to be similar to statistics anxiety. They used mathematics anxiety rating scale (MARS) to evaluate the use of humour as an intervention for statistics anxiety.

Cruise et al. (1985) were one of the first researchers to advocate a distinction between Mathematics Anxiety and Statistics Anxiety. They argued that the existing measures of mathematics anxiety did not adequately assess all aspects of statistics anxiety, and they developed the Statistical Anxiety Rating Scale (STARS) to address this need. Furthermore, statistics learning has often been conceptualised as a second language learning (Lalonde and Gardner, 1993; Onwuegbuzie and Wilson, 2003) rather than mathematics learning. This notion was supported by findings that linguistic intelligence, in addition to mathematical intelligence, is related to lower statistics anxiety (Onwuegbuzie et al., 1997). Subsequently, similarities and differences between mathematics anxiety and statistics anxiety in terms of definitions, antecedents, nature, effects and interventions were documented (Baloglu, 2004).

When students approach any type of mathematical situation, such as a mathematics or statistics class, their mathematics self-concept will naturally be involved (Bandura, 1986). Mathematics self-concept is an aspect of one's attitude toward mathematics that may also include evidence of preferences for mathematics, a tendency to avoid or be attracted to mathematics, and a belief that mathematics is either useful or useless (Bandura, 1986; Ma and Kishor, 1997).

Students lacking a foundation in mathematics and quantitative reasoning may be more likely to develop negative attitudes and beliefs about mathematics and the quantitative reasoning involved in statistics. This may result in a lack of self-confidence in situations involving mathematics and statistical reasoning. Identifying individuals lacking foundational skills and holding negative attitudes is essential to creating statistical literacy (Richardson and Woolfolk, 1980). Zeidner (1991) stated that statistics anxiety influences an individual's level of performance in an undergraduate statistics class and leads to students' tendency to avoid classes involving statistics. In addition, Sutarso (1992) concluded that statistics performance is influenced by anxiety, computer and mathematics skills, as well as statistical pre-knowledge.

1.2 Problem Statement

- A vast amount of research has been conducted pertaining to statistics anxiety. However, numerous contradictory findings exist concerning the correlates of statistics anxiety. These correlates include, but are not limited to, gender, statistics experiences, attitude toward statistics and mathematics self-concept. Research on statistics anxiety and attitude toward statistics has found mixed results regarding gender differences. Some research has indicated that females experience greater levels of statistics anxiety and lower efficiency toward statistics than males. Other research has found no gender differences in statistics anxiety and attitude toward statistics.

- The purpose of many research studies was to develop and validate instruments that assess multiple dimensions of statistics anxiety, students' attitude toward statistics and students' mathematical self-concept. However, only a few studies could be found in the literature that examined the relationship between statistics anxiety, attitude toward statistics and mathematics self-concept.

- There is a lack of research on the effect of statistics anxiety, attitude toward statistics and mathematics self-concept on students' performance at South African higher education institutions.

- Statistics anxiety is a personal characteristic which has a debilitating effect on statistics academic performance and student's sense of self-worth. In addition, this challenge is compounded because it contributes to perceptions and attitudes that perpetuate a dislike for statistics and a lack of confidence when doing statistics exercises or problems. Hence there exists a need to re-emphasise the importance of statistics anxiety as a problem which affects the statistical development of students.

1.3 Research Questions

With regard to the given problems, it was deemed important to incorporate an objective measurement of statistics anxiety in order to obtain more concrete results about statistics anxiety. This led to the following research questions:

- *What is the effect of statistics anxiety, attitude toward statistics and mathematics self-concept on students' performance in an introductory statistics course?*
- *Is there a relationship between statistics anxiety, attitude toward statistics and mathematics self-concept?*
- *Are there any gender differences regarding statistics anxiety, attitude toward statistics, mathematics self-concept and performance?*
- *Do students become less or more anxious over the course of the semester?*
- *Do students' attitude toward statistics and mathematics self-concept change over the course of the semester?*

1.4 Aim and Objectives of the Study

The primary aim of this study was to examine the association of statistics anxiety, attitude toward statistics and mathematics self-concept with regard to performance in an introductory statistics course. Specifically, the aim was to determine whether or not statistics anxiety affect students' performance. In addition, the study aimed to determine whether statistics anxiety, attitude toward statistics and mathematics self-concept differs by gender and to investigate the experiences and opinions of students regarding statistics anxiety.

The above aims were realised by pursuing the following objectives:

1. To statistically investigate the effects and relationships between statistics anxiety, attitude toward statistics anxiety, mathematics self-concept and academic performance.

2. To statistically investigate gender differences regarding statistics anxiety, attitude toward statistics and mathematics self-concept.

3. To establish and identify critical elements of the trend of statistics anxiety, attitude toward statistics and mathematics self-concept over the course of the semester.

4. To gather qualitative information on the experiences and opinions of students regarding statistics anxiety and their attitude toward statistics by means of interviews.

1.5 Research Hypotheses

For the purpose of the empirical study, the related research questions were transformed into the following hypotheses:

H_0a: No association between statistics anxiety, attitude toward statistics, mathematics self-concept and students' performance.
H_1a: There is an association between statistics anxiety, attitude toward statistics, mathematics self-concept and students' performance.

H_0b: Statistics anxiety, attitude toward statistics, mathematics self-concept and performance between males and females do not differ.
H_1b: Statistics anxiety, attitude toward statistics, mathematics self-concept and performance between males and females differ.

H_0c: Students' statistical anxiety, attitude toward statistics and mathematics self-concept remains the same during the course of the semester.
H_1c: Students' statistical anxiety, attitude toward statistics and mathematics self-concept changed during the course of the semester.

1.6 Assumptions

This research was based on the assumption that participants would provide honest and accurate answers in the survey and give honest responses about their experiences regarding statistics anxiety, attitude toward statistics and mathematics self-concept. It was my assumption that lectures would look forward to learn about my findings and recommendations as opportunity for them to reduce students' anxiety toward statistics. In addition, this research was based on the assumption that statistics anxiety is a disabling condition for which lectures have developed strategies to cope (or perhaps overcome) in order to help students achieve their full potentials in statistics.

1.7 Research Design and Methodology

This section summarises the research design and methodology employed in the study; also this section briefly describes the methods and procedures adopted in the empirical (main quantitative) study undertaken. More detail regarding these methods and procedures are provided in Chapter 3.

1.7.1 Identification of variables

In this study the dependent variable is an average *Performance* in a business statistics course. For the purpose of this study the independent variables were *Statistics Anxiety, Attitude toward Statistics* and *Mathematics Self-concept.* The confounding variables were student's age and student's class attendance.

1.7.2 Research design

For this study, the research design falls within the paradigm of quantitative research. For the purpose of this research a non-experimental research design was used where the researcher used data (test marks, examination marks and questionnaire results) to test the relationship between variables as well as to test the formulated hypotheses. The quantitative paradigm was considered appropriate for this study as the research involved the collection of numerical data and various statistical methods were used to analyse the data. In addition, qualitative research was conducted. Semi-structured interviews (conducted with six students in a business statistics course) were used to gather the data. Open ended questions were used to allow qualitative opinions and experiences.

1.7.2.1 Population and sampling

In this study a non-probability sampling method was used as the participants were selected on the basis of their availability. First, convenience sampling was employed because the introductory statistics students were easily accessible and they were available at a given time. Secondly, judgement sampling was employed according to the following criteria: (i) participants had to complete all three questionnaires during the course of the study and (ii) participants had to obtain a mark for both tests as well as an examination mark. The accessible population in this study comprised of 103 introductory business statistics students. For the purpose of conducting semi-structured interviews, six students were randomly selected from the initial sample of participants.

1.7.2.2 Data collection

The main source of data was the researcher's records of the Statistical Anxiety Rating Scale (STARS) instrument results and student performance in the course. The qualitative data was obtained by conducting semi-structured interviews with six students. The quantitative data were analysed with the aid of the Statistical Package for the Social Science (IBM SPSS Version 24) and SAS software (SAS Version 9.4).

1.8 Concept Clarification

Throughout the study a number of keywords, terms and concepts are used, normally within a particular context. Because of the complex nature of educational and statistical concepts, results that might appear clear to the researcher could mean different things to the reader. In order to avoid confusion, the key concepts that need to be defined and explained for the purpose of this study are listed below.

Statistics: The science that deals with the collection, classification, analysis, and interpretation of numerical facts or data. Statistics provides techniques to make sense or meaning of the data. Statistical tools (techniques) not only summarise past data, but can predict future events as well. Statistics provides tools for decision making in the face of uncertainty (probability).

Statistics education research: Research that focuses on the teaching, learning and assessment of statistics at all levels. The purpose of the research is to improve teaching practice, students' understanding of and performance in statistics, as well as students' statistical thinking and reasoning.

Statistics course/module: The researcher wants the reader to note that the terms module and course have the same meaning for the purpose of this study. A statistics course/module is a unit of education or teaching in which a single topic (statistics in this case) is studied for a given period of time (e.g. semester, one year, etc). This unit, together with other such completed units, can count towards a particular qualification. A unit usually consists of lessons, lectures, practical sessions, teaching materials, objectives, directions for use, and test items.

Empirical investigation: According to Babbie and Mouton (2001) research can be described as empirical when a researcher makes use of either primary data (e.g experiments, surveys, case studies) or existing data (e.g content analysis, historical studies). Empirical investigation as used in this study, specifically refers to the research undertaken that is based on primary data collection by means of a questionnaire survey and interviews.

Statistical concept: Statistical concepts can be seen as the meaning of terms, topics, and names of variables used in statistics education and statistics production. A statistical concept is organised around a main idea of unit in which one thinks. Some general concepts used in an introductory statistics course are for example probability, confidence interval, hypothesis test, regression, or analysis of variance.

Academic performance: This concept can be defined by marks that students obtain for registered subjects at a tertiary institution. The terms "achievement", "performance" and "academic performance" will be used interchangeably for the purpose of this study.

Tutorials: A tutorial is a method of transferring knowledge and may be used as part of learning process in the field of education. It is more interactive and specific than lectures, class notes or books. Tutorials seek to teach by illustrations and examples and supply the information to complete a certain task.

Study attitude: Study attitude is a vague concept, but for the purpose of this research it may be seen as the students' orientation towards their studies. This orientation will then explain their actions towards learning and the effort that they put into their studies.

Success: In this study, success refers to earning a passing grade in a module or subject.

Self-concept: For the purpose of this research self-concept was defined as an individual's general composite or collective views of themselves across multi-dimensional sets of domain specific perceptions.

1.9 Chapter Layout

This dissertation is organised into five chapters. This document aims to present the research in a rigorous structure. Such a structure makes it easier to locate relevant information and lowers the risk of missing information. The research is presented as follows:

Chapter 1 has provided a brief orientation that includes background perspectives and important aspects related to the research design and methodology.

Chapter 2 consists of a literature study pertaining to statistics anxiety, its correlates and the extant instruments utilised to measure it. Literature regarding comparison of statistics anxiety and mathematics self-concept and physiological symptoms are also discussed.

In **Chapter 3** the research design that was selected for this research is discussed. Moreover, the research methodology is described with specific references to the data collection process, methods and the instruments that were used for the empirical investigation.

Chapter 4 contains the results that were obtained from an analysis of the data collected through STARS questionnaire and follow up face-to-face interviews. The chapter gives a thorough description and analysis of the research that has been conducted to investigate the association of statistics anxiety, attitude toward statistics and mathematics self-concept with performance in a business statistics course. Some results or findings are presented with tables and figures and the emerging themes from the interviews are described.

In conclusion, **Chapter 5** provides a condensed summary of the main findings of the literature review and the empirical investigation, together with recommendations for further research.

Also included are the STARS questionnaire and interview questions developed by the researcher during the course of the study. These documents appear in the appendices and provide important background to the study. The appendices are as follows:

Appendix A: STARS Questionnaire.
Appendix B: Interview Questions.

1.10 Conclusion

This chapter provided an overview of what the research entails. The chapter started by providing a brief background which included literature about statistics anxiety and the contradictory findings in relation to its comparisons with mathematics anxiety and its correlates. The problem statement, research questions and research goals were specified. Next, research hypotheses, assumptions and concept clarification leading to the research study were discussed. Following these was a brief discussion on the methodology and the outline of the chapters in the dissertation.

The next chapter, provides literature studies which are related to this research study.

Chapter 2

Literature Review

"...statistics anxiety is an element of a performance characterised by extensive worry, intrusive thoughts, mental disorganisation, tension, and physiological arousal... when exposed to statistics content, problems, instructional situations, or evaluation contexts, and is commonly claimed to debilitate performance in a wide variety of academic situations by interfering with the manipulation of statistics data and solution of statistics problems" (Zeidner, 1991, p. 319).

2.1 Introduction

In this chapter the results of a literature review on statistics anxiety, attitude toward statistics and mathematics self-concept will be presented. Numerous definitions have already been discussed in Chapter 1 and will therefore not be repeated in this chapter. The main objective of this literature review is to investigate the effects of statistics anxiety, attitude toward statistics and mathematics self-concept on statistics performance. Different anxiety rating scales will also be investigated and discussed.

The question of the impact of statistics anxiety on performance remains open as other questions come to mind. Are there any gender differences regarding statistics anxiety? How does students' attitude towards statistics affect their anxiety? Can the use of various treatments reduce statistics anxiety? How is statistics anxiety related to learning behaviour and to what degree is it related to students' deposition, attitudes or experiences? What factors may influence statistics anxiety? This study will endeavour to answer these questions and to advance the understanding of the role and impact of statistics anxiety in higher education.

In a review of literature on statistics anxiety, Shah Abd Hamid and Sulaiman (2014) identified statistics anxiety as a challenge for both teachers and learners. According to researchers, statistics anxiety is negatively related to students' performance in the course (Macher et al., 2012) as well as in academic research courses (Williams, 2010). Consequently, with statistical literacy as a goal, an increasing number of degree programs are making statistics courses mandatory for university students (Williams, 2010). Unfortunately, taking a statistics course is often a negative experience for most students in non-mathematical disciplines (Onwuegbuzie and Wilson, 2003). The study of Shah Abd Hamid and Sulaiman (2014) indicated that there are students who are not good in mathematics and who are not interested in studying it. The study also reflected students' anxiety towards statistics. From 2010 to 2013, over a period of six semesters, the average failure rate for a statistics course at the specific department was 16.20% (min=4.17%, max=26.83%). In three of those semesters, the failure rates were high compared to other undergraduate courses offered in the same semester. Their study was conducted to provide empirical evidence of students' anxiety towards statistics. They found that students taking the statistics course had high levels of statistics anxiety.

Cruise and Wilkins (1980) articulate that students may experience anxiety due to low efficacy perceptions in the subject (personal factor). Moreover, their low efficacy may be due to poor instruction or poor knowledge of technology (environmental factor). This chapter will also explore how students' anxiety (personal factor) toward statistics can be reduced by modifying instruction (environmental factor) that mostly builds self-efficacy through providing feedback.

2.2 Extraction of Sources

The search for sources for the literature review was conducted using three scientific databases; namely the ERIC (Education Resources Information Center) database, the PsycINFO database and the ACAD (Expanded Academic Index). The ERIC database provides a comprehensive Internet-based bibliographic and full-text database of education research and information. It database covers journal articles, books, conference papers, technical reports and policy papers for the period 1966 until present. PsycINFO is an electronic bibliographic database providing abstracts and citations to scholarly literature in the psychological, social, behavioural and health sciences from 1890 up to the present. About 80% of the database comprises scholarly, peer-reviewed journal articles, while the remainder of the database consists of book chapters, technical reports and dissertations. ACAD is a multi-disciplinary index to scholarly academic articles on a wide variety of subjects. ACAD covers publications dating from 1980 to the present.

The above-mentioned databases were searched using free-text searching with keywords such as *statistics education, statistics and teaching methods, statistical learning and statistics* and *instruction.* This process identified several hundred documents. A more advanced search then used keywords such as *academic performance, statistics anxiety, statistics education research, academic anxiety, mathematics anxiety, reliability, gender differences, learning strategies, attitude, examination anxiety, asking for help anxiety* and *interpretation anxiety.* The documents identified in this way were inspected, and irrelevant documents and duplicate references were eliminated. The references of the relevant documents were then manually searched for other potential articles of interest.

2.3 Statistics Anxiety vs Mathematics Anxiety

When statistics anxiety was first identified, researchers conceived the construct to be similar to mathematics anxiety (Schacht and Stewart, 1990). As stated in Chapter 1, the MARS was used to evaluate the use of humour as an intervention for statistics anxiety. According to the literature, both statistics anxiety and mathematics anxiety are highly common among students and researchers. There is however a contradiction in the literature about the relationship between statistics anxiety and mathematics anxiety. Baloglu (2004), for example, indicates that statistics anxiety is hypothesised to be closely related to mathematics anxiety with some researchers stating that statistics anxiety has the same construct as mathematics anxiety. The frequent appearance of statistics courses within mathematics departments and statistically significant relationships between mathematics anxiety and statistics anxiety may be the two main reasons for this (Dew et al., 1984; Gal and Ginsburg, 1994).

On the other hand, some researchers are of the opinion that statistics anxiety should be defined as a separate entity. It has been hypothesised that most of the learners' difficulties in statistics may not be as a result of insufficient intellectual ability or aptitude; but, rather, they may be reflections of attitudinal factors such as misconceptions (Brayne et al., 1995), negative attitude (Wise, 1985), and anxiety (Gal and Ginsburg, 1994). Therefore, Statistics anxiety has been defined by these researchers as one type of situation anxiety.

Similarly, a number of researchers (Cruise et al., 1985; Benson and Bandalos, 1988; Benson, 1989; Zeidner, 1991; Onwuegbuzie, 1993; Birenbaum and Eylath, 1994; Gadzella and Baloglu, 2001) argue that, even though statistics anxiety and mathematics anxiety are somehow related, statistics anxiety is hypothesised to be a distinct entity from mathematics anxiety. Likewise, Onwuegbuzie (1993, p. 81) concludes that "... there is little doubt that statistics anxiety needs to be considered and measured separately." Nonetheless, the nature of statistics anxiety and its relationships with other constructs have not been fully investigated. According to Wentzel

(1998), it would appear reasonable to postulate that a relationship exists between mathematics anxiety and statistics anxiety, but there is not enough research which demonstrates the specific degree to which this is a correct assumption.

2.3.1 Differences between statistics anxiety and mathematics anxiety

Several studies have revealed that there are major differences between mathematics and statistics regarding the cognitive processes involved. According to Cruise et al. (1985), statistics involves different mental procedures and requires more than the manipulation of mathematical symbols. They also observed that students who had difficulties in statistics displayed characteristics different from students who had difficulties in mathematics. Buck (1987) explained that even though statistics employs basic mathematical concepts, it is more closely related to verbal reasoning than mathematical reasoning. Similarly, Zerbolio Jr (1989) emphasised that one uses more logical skills than mathematics skills to solve statistical problems. Moreover, the cognitive processes involved with statistics anxiety may be different from the cognitive processes involved with mathematics anxiety.

Birenbaum and Eylath (1994) and Barkley (1995) articulate that, unlike mathematics anxiety, statistics anxiety is significantly correlated with inductive reasoning ability. Cruise et al. (1985) and Bradstreet (1996) speculate that the concept of statistics anxiety may be broader than that of mathematics anxiety. In addition, Onwuegbuzie et al. (1999) state that "...students with high levels of mathematics anxiety tend to have high levels of statistics anxiety, but the converse is not necessarily true".

2.3.2 Similarity between statistics anxiety and mathematics anxiety

While some researchers believe that there is a difference between statistics anxiety and mathematics anxiety, others consider mathematics anxiety and statistics anxiety to be of the same family. According to Richardson and Suinn (1972), Dew et al. (1984) and Cruise et al. (1985), both mathematics anxiety and statistics anxiety are classified as situation-specific, content oriented, and trait and state specific. Sherard (1981) and Zeidner (1991) also indicate that mathematics and statistics are comprised of few easily identifiable elements like emotional elements and elements characterised by worry. In addition, the dimensions of statistics anxiety and mathematics anxiety show some similarity.

Research has also demonstrated a moderate association between statistics anxiety and mathematics anxiety. Birenbaum and Eylath (1994) investigated the relationship between statistics anxiety and mathematics anxiety. They found that statistics anxiety was significantly associated to mathematics anxiety (r=0.54, p<0.001). They also found that inductive reasoning ability was the only variable that was significantly associated to statistics anxiety (r=-0.26, p<0.01) but not associated to mathematics anxiety (r=-0.10, p>0.05).

Even though mathematics anxiety was initially hypothesised as a unidimensional construct (Richardson and Suinn, 1972), it was later found to be multidimensional (Cruise et al., 1985; Alexander and Martray, 1989; Satake and Amato, 1995). In the literature there seems to be an agreement regarding the classification of the antecedents of both statistics anxiety and mathematics anxiety. According to Byrd (1982) and Onwuegbuzie (1993), both mathematics anxiety and statistics anxiety have similar dispositional, situational and environmental antecedents. Furthermore, both mathematics anxiety and statistics anxiety have been found to have physiological, cognitive, psychological and behavioral impacts on individuals (Fennema and Sherman, 1976; Onwuegbuzie et al., 1997).

More importantly, although many studies found a significant positive relationship between statistics anxiety and mathematics anxiety, the relationship is moderate and mathematics anxiety, at a maximum, explained less than 50% of the variance in statistics anxiety (Baloglu, 2004).

2.4 Statistics Anxiety Rating Scales

The literature revealed six measures aimed to assess statistics anxiety. They are the Statistical Anxiety Rating Scale (STARS) (Cruise et al., 1985), the Statistics Anxiety Inventory (Zeidner, 1991), the Statistics Anxiety Scale (Pretorius and Norman, 1992), an unnamed instrument (Zanakis and Valenzi, 1997), the Statistics Anxiety Measure (Earp, 2007), and the Statistical Anxiety Scale (Vigil-Colet et al., 2008). These measures and their sub-scales are summarised in Table 2.1.

Table 2.1: Measures and Sub-scales of Statistics Anxiety (By Date of Publication)

Measure	Sub-scales
51-items STARS (Cruise et al., 1985)	Interpretation Anxiety Test and Class Anxiety Fear of Asking for Help Worth of Statistics Computation Self-Concept Fear of Statistics Teachers
40-item Statistics Anxiety Inventory (Zeidner, 1991)	Statistics Test Anxiety Statistics Content Anxiety
10-item Statistics Anxiety Scale (Pretorius and Norman, 1992)	Unidimensional
36-item unnamed instrument (Zanakis and Valenzi, 1997)	Student Interested in and perceived worth of statistics Anxiety when seeking help for Interpretation Computer Experience Mathematics Anxiety Understanding Test Anxiety
44-item Statistics Anxiety Measure (Earp, 2007)	Anxiety Attitude Towards Class Fearful Behaviour Attitude Towards Maths Performance
24-item Statistics Anxiety Scale (Vigil-Colet et al., 2008)	Examination Anxiety Asking for Help Anxiety Interpretation Anxiety

Source: Chew and Dillon (2014)

Chew and Dillon (2014) report that two of these measures assume statistics anxiety to be similar to mathematics anxiety. Both the Statistics Anxiety Inventory (Zeidner, 1991) and the 10-item Statistics Anxiety Scale (Pretorius and Norman, 1992) were developed by replacing words related to mathematics with words related to statistics. Moreover, three measures (40-item Statistics Anxiety Inventory, 10-item Statistics Anxiety Scale and 24-item Statistical Anxiety Scale) made no distinction between statistics anxiety and attitude towards statistics. However, the unnamed instrument (Zanakis and Valenzi, 1997), the Statistics Anxiety Measure (Earp, 2007) and 51-item STARS (Cruise et al., 1985) assess statistics anxiety and attitude toward statistics. According to research, these three measures might result in high correlations among statistics anxiety, mathematics anxiety, and attitudes toward statistics. Consequently, researchers might assume the constructs to be the same or even identical.

de Leeuw (2004) states that unidimensional scaling is the special one-dimensional case of multidimensional scaling. It is often discussed separately, because the unidimensional case is quite different from the general multidimensional case. It is applied in situations where the researcher has a strong reason to believe there is only one interesting underlying dimension, such as time, ability, preference or anxiety.

The two instruments that are used most often are the 51-item Statistical Anxiety Rating Scale (STARS) and the 24-item Statistics Anxiety Scale (SAS), and both will be discussed in this section. According to the literature, the STARS rating scale is the most popular because of its reliability and validity data compared to that of other measures (Chew and Dillon, 2014). The STARS, developed by Cruise and Wilkins (1980), consists of 51-items across six sub-scales. The sub-scales are designed to measure a student's (a) anxiety regarding interpreting statistics, (b) test and class anxiety, (c) fear of asking for help, (d) perception of the worth of statistics, (e) computational self-concept, and (f) fear of the statistics teacher.

The first part of the STARS assesses statistics anxiety by means of the following three sub-scales:

- Interpretation Anxiety (11 items): Anxiety of being faced with statistical data, interpretation and decision-making.
- Test and Class Anxiety (8 items): Anxiety when attending a statistics class and writing a test or examination.

- Fear of Asking for Help (4 items): Anxiety when asking the statistics teacher, a fellow student or a private tutor questions about statistical procedures.

The items of these three sub-scales are rated on a 5-point Likert scale ranging from 1= No Anxiety to 5= Very Much Anxiety. Higher scores on each sub-scale indicate higher levels of anxiety.

The second part of the STARS assesses attitude toward statistics by means of the following sub-scales:

- Worth of Statistics (16 items): Perceived usefulness of statistics.
- Computational Self-concept (7 items): Perceptions of a student's ability to do statistical computations.
- Fear of Statistics Teacher (5-items): Attitude toward statistics teacher students think that statistics teachers are inhuman.

The items of these three sub-scales are rated on a 5-point Likert scale ranging from 1= Strongly Disagree to 5= Strongly Agree. Higher scores on each sub-scale indicate higher levels of anxiety.

2.5 Cronbach's alpha and Reliability of STARS

Researchers attempt to create reliable questionnaires in order to enhance the accuracy of their assessments and evaluations. Validity and reliability are two fundamental elements in the evaluation of a measurement instrument. According to Nunnally (1978) and Tavakol and Dennick (2011), reliability is concerned with the ability of an instrument to measure consistently, and the reliability of an instrument is closely associated with its validity. According to Creswell (2002), validity refers to how well an instrument measures what is purported to measure. In addition, (Fraenkel and Wallen, 2008, p. 147) stated that "validity refers to the appropriateness, meaningfulness, correctness, and usefulness of the inferences a researcher makes.

Reliability refers to whether or not a scale consistently renders a similar measure time after time and what the scale is measuring is ascertained through determining the scale validity. Reliability is an important aspect of scale research as a scale cannot be valid if it is not reliable (DeVellis, 2016). Nunnally and Bernstein (1994) defined reliability as "the proportion of variance attributable to the true score of the latent variable". Scale reliability is an essential and an important feature of any scale as it provides a measure of a scales internal consistency or the homogeneity of the items in the scales (DeVellis, 2016). Cronbach's alpha is the most widely used objective measure of reliability (Nunnally, 1978; Nunnally and Bernstein, 1994; Fraenkel and Wallen, 2008).

Definition

Cronbach's alpha denoted by α is defined as

$$\alpha = \tfrac{P}{P-1}\left(1 - \frac{\sum_{i=1}^{P} \sigma^2_{Y_i}}{\sigma^2_X}\right), \tag{2.1}$$

where P is the number of components (items or testlets)
σ^2_X is the variance of the observed total test scores
$\sigma^2_{Y_i}$ is the variance of component i.

Cronbach's alpha (also known as the alpha coefficient or the reliability coefficient) was first developed in 1951 by Lee Cronbach in order to provide a measure of the internal consistency of an instrument or test. It is expressed as a number between 0 and 1. Point 0 means no consistency in measurement and point 1 indicates perfect consistency in measurement. According to Tavakol and Dennick (2011), internal consistency is the extent to which all the items in a test or instrument measure the same concept or construct, and it is therefore connected to the interrelatedness of the items within the instrument.

Reliability estimates show the amount of measurement error in a test. Tavakol and Dennick (2011) state that the interpretation of a reliability is the correlation of an instrument with itself. Squaring this correlation and subtracting it from 1 produces the index of measurement error. For instance, if an instrument has a reliability of 0.90, there is 0.19 error of variance (random error) in the scores (0.90^2=0.81; 1-0.81=0.19).

As the estimates of reliability increase, the fraction of a test score that is attributable to error will decrease. To calculate the effect of measurement error on the observed score of an individual student, the standard error of measurement must be calculated (SEM). According to Harvill (1991), the standard error of measurement is related to test reliability in that it provides an indication of the dispersion of measurement errors when one is trying to estimate students' true scores from their observed test scores.

Cronbach's alpha can be used for dichotomous and continously scored variables. According to Lance et al. (2006), a reliability coefficient of 0.7 or higher is considered acceptable. The value 0.70 indicates that 70% of the variance in the scores is reliable variance, therefore 30% is error variance. In addition, Nunnally (1978) states that a reliability coefficient of 0.7 or higher is acceptable for exploratory research. In basic research, the concern is with the size of correlations and with the differences it means for different experimental treatments. According to Nunnally (1978), for basic research, a reliability coefficient of 0.80 is adequate and a 0.90 reliability is the minimal acceptable in applied scenarios.

Table 2.2 presents the commonly accepted rule for describing internal consistency using Cronbach's alpha.

Table 2.2: Acceptance rule for internal consistency

Cronbach's alpha	Internal consistency
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Source: Nunnally (1978)

As the STARS instrument is the most popular one to use, five studies could be found in the literature that evaluated the reliability of this instrument by means of Cronbach's alpha.

Table 2.3 presents comparisons of Cronbach's alpha values on the STARS instrument for different studies with different sample sizes.

Table 2.3: Test and Comparison of Cronbach's alpha values on STARS

Scale	Cruise (1985)	Baloglu (2002)	Baloglu (2003)	Onwuegbuzie (2003)	Liu (2011)
Worth of Statistics	0.91	0.91	0.94	0.92	0.91
Interpretation Anxiety	0.87	0.89	0.91	0.82	0.86
Test and Class Anxiety	0.68	0.91	0.90	0.90	0.85
Computation Self-concept	0.88	0.85	0.86	0.93	0.74
Fear of Asking for Help	0.89	0.62	0.79	0.83	0.72
Fear of Statistics Teachers	0.80	0.79	0.64	0.85	0.69
Total Scale Scores	0.93	0.96	0.96	0.96	0.94

Source: Liu et al. (2011)

Liu et al. (2011) observed a minimum reliability of 0.69 on Fear of Statistics and a maximum reliability of 0.91 on Worth of Statistics, for a total scale score of 0.94, which indicated that the STARS instrument was highly consistent. Baloglu and Zelhart (2003) observed a minimum reliability of 0.64 on Fear of Statistics and a maximum reliability of 0.94 on Worth of Statistics. Baloglu (2002) reported a minimum reliability coefficient 0.62 on Fear of Asking for Help and a maximum reliability of 0.94 on Worth of Statistics. Cruise et al. (1985) reported the minimum internal consistencies of 0.68 on Test and Class Anxiety and maximum reliability of 0.94 on Worth of Statistics. Lastly, Onwuegbuzie and Wilson (2003) reported a minimum reliability score of 0.82 on Interpretation Anxiety and a maximum reliability of 0.93 on Computational Self-concept.

Note that four of the five studies had a maximum reliability on Worth of Statistics. The STARS has been found to possess good psychometric properties in all 5 studies shown in Table 2.3, because their reliability Scores were all highly consistent.

Another statistics rating scale frequently used in the literature is SAS (Vigil-Colet et al., 2008), which was developed to assess three aspects of anxiety. It consists of the first three sub-scales of the STARS: Examination Anxiety, Asking for Help Anxiety and Interpretation Anxiety. The aim was to develop an instrument that was shorter than STARS and that specifically focuses on statistics anxiety. Each sub-scale consists of eight items, for a total of 24 items. Twelve items were adapted from STARS, and 12 items are completely new. The items are rated on a 5-point Likert scale, ranging from 1= No Anxiety to 5= Considerable Anxiety. The values of the alpha coefficient show that the reliability of the sub-scales and the overall scale is acceptable (Examination Anxiety= 0.874, Asking for Help Anxiety= 0.924, Interpretation Anxiety= 0.819 and the Overall scale= 0.911).

2.6 Statistics Anxiety and Performance

According to Onwuegbuzie et al. (1997), statistics anxiety is the apprehension which occurs when individuals encounter statistics in any form and at any level. Furthermore, statistics anxiety is situation-specific as the symptoms only emerge at a particular time and in a particular situation, when learning or applying statistics in a formal setting (Zeidner, 1991; Onwuegbuzie et al., 1997).

Research has revealed that most university students are required to enroll or register for statistics courses or quantitative research methodology courses as a necessary part to complete their degree program. Research also points to an increase in the number of articles on statistics anxiety in recent years. In the literature it is also stated that researchers have recognised that statistics anxiety is a multidimensional construct that has negative implications or effects on academic performance.

Onwuegbuzie and Wilson (2003) further state that between two-thirds and four-fifths of graduate students appear to experience uncomfortable levels of statistics anxiety. Other researchers agree that, for many university students, statistics is one of the most anxiety-inducing courses in their curriculum (Caine et al., 1978; Lundgren and Fawcett, 1980; Blalock Jr, 1987; Zeidner, 1991).

Shah Abd Hamid and Sulaiman (2014) used STARS as their measure of anxiety. The 139 participants consisted of 26 males (18.7%) and 113 females (81.3%) recruited from students enrolled in a statistics course. The sub-scale with the highest level of anxiety was Fear of the Statistics Teacher (81.92%), followed by Test and Class Anxiety (75.03%), Asking for Help (66.67%), Interpretation of Data Anxiety (65.38%), Computation Self-concept (62.43%) and Worth of Statistics (43.62%). The sub-scales had interval consistency coefficients, ranging from 0.73 (Teacher of Statistics) to 0.91 (Worth of Statistics).

As scores on five sub-scales were more than 50%, the students seemed to have a high level of statistics anxiety. The students in this study were the least anxious about the worth of statistics, which might have been as a result of perceived importance of statistics, which is a required course for them. However, this study did not reveal significant correlations between statistics anxiety and course performance. In addition, Finney and Schraw (2003) reported that general test anxiety is not related to student performance in statistics.

Onwuegbuzie (2004) surveyed 135 education graduate students concerning statistics anxiety and academic procrastination. He found that as many as 45% of the students reported procrastination problems in areas such as reading assignments, studying for tests, and writing papers. Additionally, the author found that procrastination was significantly related to four sub-scales (*Computational Self-concept, Fear of Asking for Help, Test and Class Anxiety* and *Worth of Statistics*) of statistics anxiety, though no casual relationship was implied.

According to Onwuegbuzie (1998), statistics anxiety is extremely prevalent among graduate students, especially among women and minorities. Onwuegbuzie and Wilson (2003) claim that a significant proportion of students do not complete their theses or dissertations because of statistics anxiety, and therefore do not obtain their graduate degrees. Cesari (1990) and Bowen and Rudenstine (1992) affirm that statistics anxiety in part may prevent some graduate students from completing their degrees.

Ali and Iqbal (2012) believe that statistics anxiety can have drastic effects on students as they can experience deterioration in their performance in class which can lead to low self-efficacy in activities related to statistics. They conducted a study with 66 psychology major students at the University of Karachi to test three hypotheses: (a) the higher the score on statistics anxiety, the lower the marks in a statistics examination, (b) students who feel comfortable in doing mathematical calculations will score less on statistics anxiety as compared to those who do not feel comfortable with mathematical concepts, and (c) students who feel comfortable using scientific calculators will score less on statistics anxiety as compared to those who feel uncomfortable using it.

The study was conducted on the day of examination for the statistics subject after the completion of the examination paper. All those who volunteered were required to complete the demographic information sheet along with the Statistics Anxiety Scale (Vigil-Colet et al., 2008). For hypothesis testing, Pearson's correlation and t-tests were applied. The results showed a moderate negative and statistically significant correlation between statistics anxiety and examination marks (r= -0.551, $p< 0.001$). Ali and Iqbal (2012, p. 116) therefore claim that "statistics anxiety lowers performance of students, which further increases their anxiety." Furthermore, the results of the study support the hypothesis, that confidence in mathematical calculations would decrease overall statistics anxiety. However, the third hypothesis was statistically significant for only one domain of SAS (Examination Anxiety). The comfort in using a calculator would not necessarily reduce overall statistics anxiety.

Other researchers found similar results. Dillon (1982), Blalock Jr (1987) and Onwuegbuzie and Seaman (1995) found a negative relationship between statistics anxiety and students' learning and performance in statistics-related courses. Benson (1989) found that most college students showed lower levels of test anxiety in other courses than in statistics modules. Musch and Broder (1999) found that statistics examinations are more anxiety-inducing than other examinations.

Onwuegbuzie and Wilson (2003) reported that statistics anxiety may impair performance by interfering with students' ability to receive, concentrate on, and encode the terms and concepts presented in class. In addition, Mji (2009) admits that statistics anxiety may have negative implications for the acquisition of skills, knowledge and strategies identified as necessary for students' prospective careers. Research has also shown that students with statistics anxiety feel challenged in pursuing statistics courses. This in turn adds to their pressure which contributes highly to their poor performance.

The studies cited above have all examined linear relationships between anxiety and student performance. However, Keeley et al. (2008) conducted a study through which they explored the possibility of a curvilinear relationship between statistics anxiety and performance among undergraduate students.

Participants were students enrolled in an introductory statistics course for the social sciences. Their performance on each of six tests across the semester was recorded. In addition, there were seven administrations of STARS to measure the students' statistics anxiety, one at the beginning of the course and then directly after each of the six tests. Only those students who wrote all six tests and completed all seven STARS measures were analysed (n=*38*). Keeley et al. (2008) also examined the reliability of the STARS scores and found that STARS scores are a reliable measure of statistics anxiety.

Figure 2.1 shows the patterns of the six anxiety sub-scales of STARS over the course of the semester. There was a statistically significant drop across time on each scale. Students therefore became less anxious about the learning of statistics. According to Figure 2.1, Test and Class Anxiety scores were higher than all other scales, while Fear of the Statistics Teacher scores were lower than all the other scales.

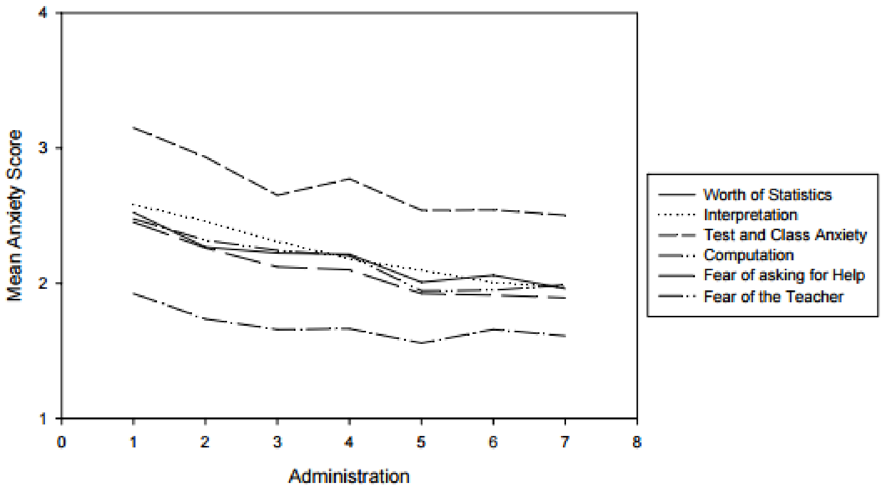


Figure 2.1: *(Adapted from keeley et al. 2008)* Students' average anxiety scores for each scale across the seven administrations.

They also reported results from a repeated measures ANOVA which indicated that students' written test scores decreased across the term; $F(4.13,\ 289.38) = 29.31$, p-value < 0.001. Each written test was found to be normally distributed, but the written test scores did not evidence adequate sphericity, so they examined the Greenhouse-Geisser correction. Some written test scores dropped more than others (see Figure 2.2). To examine these differential drops, they conducted post-hoc contrasts within the same repeated measures ANOVA. Students' performance in Test 1 was found to be approximately equal to their performance in Test 2. However, they found a statistically significant decline from Test 2 to Test 3. Test 3 and Test 4, as well as Test 4 and Test 5, were approximately equal. Lastly, they found a statistically significant drop from Test 5 to Test 6.

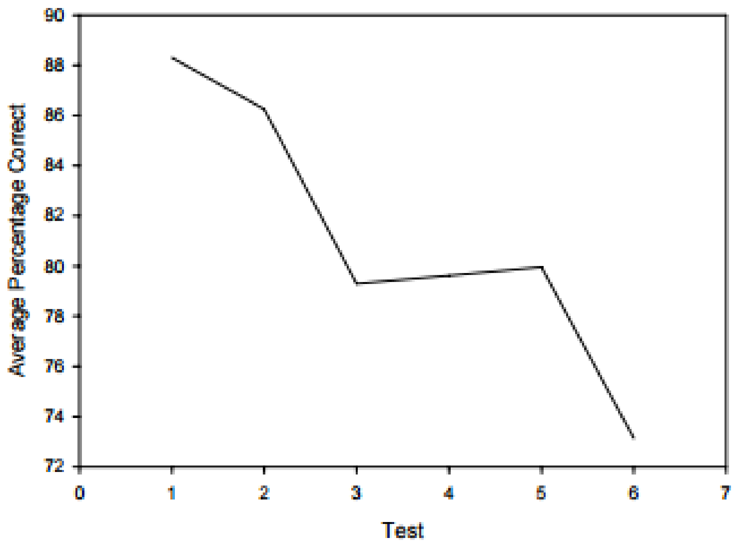


Figure 2.2: *(Adapted from keeley et al. 2008)* Students' average test scores across the six exams.

Although the fact that students' anxiety dropped and test scores decreased may seem like a contradiction, students' anxiety scores and test performance became more strongly related as the term progressed. Keeley et al. (2008) also found that the relationship between statistics anxiety and performance was quadratic, rather than linear.

2.7 Factors that Influence Statistics Anxiety

There are several factors that contribute to statistics anxiety. Pan and Tang (2005) decided on four factors: fear of mathematics, lack of connection to everyday life, pace of instruction, and attitude. Onwuegbuzie and Wilson (2003) classified the antecedents of statistics anxiety into three categories: situational factors, dispositional factors and environment factors.

- Situational factors: All factors that surround the stimulus, such as prior knowledge of statistics and the status of the course.
- Dispositional factors: Factors that an individual brings to the setting, such as mathematics self-concept and self-esteem.

- Environment factors: Characteristics such as gender and racial differences, or preconceptions based on events that occurred in the past.

The lower the relationship reported between statistics anxiety and trait anxiety seem to indicate that most of the variance of statistics anxiety is due to other factors such as procrastination (Walsh and Ugumba-Agwunobi, 2002), mathematics skills (Musch and Broder, 1999), perfectionism (Onwuegbuzie et al., 1999), achievement expectation levels (Onwuegbuzie and Wilson, 2003) and statistics self-efficacy (Finney and Schraw, 2003).

Zeidner (1991) found that statistics anxiety levels among students, especially the ones from non-mathematics backgrounds, may be higher than those students with sufficient mathematical background. Pan and Tang (2005) showed that students having inadequate prior statistical or mathematical background may have noticeably higher levels of statistics anxiety as a result of worry, fear or curiosity.

Some conclusions regarding statistics anxiety have been based on researchers' personal interpretation and findings from students. For example, Malik (2015) conducted a phenomenological study using interviews, and conclusions were based on what students with limited statistical background think. She studied students' perceptions of statistics anxiety including factors that she believed contributed to statistics anxiety as well as factors that reduces statistics anxiety. A sample was drawn from undergraduate students enrolled in an introductory statistics course. Six students aged 18 and above participated in her study, in which a modified version of the Mathematics Attitude Scale (Fennema and Sherman, 1976) was used to test students' statistics anxiety.

Data were collected by means of three questions:

1. What are the specific situations that trigger intense feelings of statistics anxiety among undergraduates?

2. What factors do undergraduates believe contribute to their heightened levels of statistics anxiety?

3. What factors do undergraduates believe contribute to their reduced levels of statistics anxiety?

The framework was based on Crotty's model (1998), which involves four elements of social research, namely epistemology, theoretical perspective, methodology and methods. Each participant was interviewed individually for approximately 50 minutes. In response to the first question, the first three participants stated that *seeing a new formula or unfamiliar material causes them to feel anxious.* The other two stated that *they tend to be more anxious during exams because of the grade and pressure*, while the last participant stated that she *feels anxious whenever she begins to solve a statistical problem because she is always scared her answer might be incorrect*, which is sometimes known as self-doubt. This student also mentioned that *speaking in front of the class either in the form of a presentation or problem solving results in increased statistics anxiety.* These responses align with the findings from Williams (2010). He concluded that many students with statistics anxiety experience high levels of discomfort in the following situations: 1) notes taking during class lectures, 2) writing tests, and 3) doing statistical computations and interpretations.

Malik (2015) also considered factors that seem to heighten statistics anxiety (the second question). According to the analysis of the interview data, four themes emerged:

- Inability to decode terminology and symbols: In most cases students find it hard to make sense out of statistical formulas and symbols the first time they encounter them. According to Malik (2015), the participants conceive statistical terminology and symbols as a foreign language.

- Feelings of inadequacy: These feelings can include *lack of confidence, incompetence, frustration, flustered thoughts, worry, intimidation, confusion, fear of the unknown, apprehensive, panic, being overwhelmed, blank mind* and *trouble* *focusing*. Blalock Jr (1987) and Dillon (1982) confirm these findings by stating that statistics anxiety affects students' performance in statistics classes, and causes feelings of inadequacy and low self-efficacy for statistics related activities.

- Physiological symptoms: Symptoms expressed by participants are *increased heart rate, shaking, the urge to cry, eyes watering, deep breathing, cheeks flushing, hot face*, and *stuttering*. These symptoms are consistent with the findings of the research conducted by Onwuegbuzie et al. (1997).

- Giving up: Terms that participants used that indicate signs of giving up are *escape the moment, run out of the class, escaping, want to go away, end up skipping, give up on the test, stop trying, leaving the problem blank, get up and leave the classroom*, and *second-guess*. Zbornik (2001) found similar results. He noted that mathematics anxious students restrict themselves to one area of problem solving approaches and that these students often give up easily and skip problems that appear mildly difficult.

The visual representation of how these four themes are linked is demonstrated in Figure 2.3.

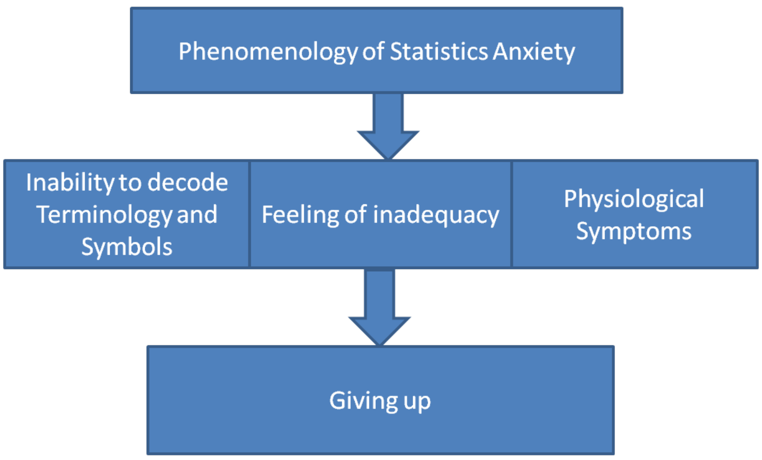


Figure 2.3: *(Adapted from Malik, 2015)* The model of Phenomenology of Statistics Anxiety.

In response to the third question, participants mentioned that the following factors reduce statistics anxiety: *taking tests in isolation, larger proportion of multiple choice questions on tests, more room to work out the problems on exam sheets, allowed to use a formula sheet, open book tests*, and *visual cues (such as diagrams or pictures).*

2.8 Implications and Effects of Statistical Anxiety

As students are faced with reasoning and analytic skill challenges in statistics courses, many researchers have identified psychological challenges that affect students' abilities to learn data analysis methods, procedures and interpretations (Baloglu, 2004; Pan and Tang, 2005; Collins and Onwuegbuzie, 2007; Bell, 2008). There is a high percentage of tertiary students who perceive statistics as one of the most stressful, feared, worrying, least enjoyed, and least understood courses in their curriculum (Onwuegbuzie and Wilson, 2003; Baloglu, 2004; Pan and Tang, 2005; Collins and Onwuegbuzie, 2007; Bell, 2008; Druggeri et al., 2008; Keeley et al., 2008; Dykeman, 2011). Collins and Onwuegbuzie (2007) state that, "Many students report higher levels of anxiety and stress in statistics courses than in any other course in their degree program," indicating a widespread emotional reaction to the subject of statistics. Dykeman (2011) reported that students rated statistics "the least desirable of all courses required for their academic major."

Other studies about statistics anxiety showed that students' reactions are mostly characterised by worry, tension and physiological symptoms of stress when they are faced with statistics classes or courses, including statistics research projects. Zeidner (1991) testified that statistics anxiety is a stimulus that produces a negatively perceived response. Thus, statistical anxiety can be an obstacle to students' learning. However, Keeley et al. (2008) defined statistics anxiety as a necessary arousal to aid students to achieve optimal performance.

Onwuegbuzie et al. (1997) confirmed that statistics anxiety appears to involve a complex array of emotional reactions which, in mild forms, may induce only small discomfort. Severe forms, however, can result in negative outcomes, such as apprehension, fear, nervousness, panic and worry. A qualitative study conducted by Onwuegbuzie et al. (1997) explored students' attitude towards statistics and perceived experiences in an intermediate statistics class by means of interviews, focus groups and journal writing. Twenty-one students participated in the study. Students reported psychological symptoms such as *depression, frustration, panic,* and *worry*, as well as physiological signs of *headaches, muscle tension, perspiration,* and *"feeling sick"*. Observations by one of the researchers as a participant-observer revealed anxious behaviours such as *nail bitting, anger,* and *tears*.

2.9 Statistics Anxiety and Attitude Toward Statistics

Similar to the lack of distinction between statistics anxiety and mathematics anxiety, "the literature makes little if any distinction between the concepts of attitudes and anxiety and the terms are often used interchangeably" Nasser (2004, p. 3).

Ajzen (1989) and Schau (2003) define attitude as "an individual's disposition to respond favourably or unfavourably to an object, institution, or event, or to any other discriminable aspect of the individual's world." According to Gal et al. (1997), attitude towards statistics represent a summation of emotions and feelings expressed over time in the context of learning mathematics or statistics. Ajzen (1989) states that, although formal definitions vary, most contemporary social psychologists seem to agree that the characteristic attribute of attitude is its evaluative (positive or negative) dimensions. Schau (2003) states that attitude toward statistics have been conceptualised as a multidimensional construct consisting of two factors: (a) Attitude toward Field and (b) Attitude toward Course. Attitude toward Field refers to students' attitudes towards the usefulness of statistics in general or in terms of their field of study, whereas Attitude toward Course refers to students' attitude towards statistics as a course on its own.

Lalonde and Gardner (1993) found that learning statistics was indirectly affected by students' anxiety, because of the impact that anxiety has on students' attitude towards statistics. Onwuegbuzie and Seaman (1995) and Onwuegbuzie et al. (1997) confirm that statistics anxiety brings about students with a lower ability to understand research articles, data analysis, and interpretation of analyses. According to Schau (2003) many students express a strong negative attitude when they enter their required introductory statistics course. It has, however, been observed by researchers that many students see statistics as an overwhelming learning and survival task that causes a great deal of stress (Onwuegbuzie et al., 1999; Schau, 2003). Gal et al. (1997) reveal that students that hold and express negative attitudes can create an uncomfortable classroom climate.

Gal et al. (1997) indicate that students' attitudes and beliefs regarding statistics deserves attention for three reasons: 1) their role in influencing the teaching or learning process (process consideration), 2) their role in influencing students' statistical behaviour after they leave the classroom (outcome consideration), and 3) their role in influencing whether or not students will choose to enroll in a statistics course later on, beyond their first encounter with statistics (access consideration). Furthermore, researchers believe that students are not ready to embrace and function within a problem-solving oriented learning environment in statistics education. Gal et al. (1997) claim that this is due to students' attitudes from their experiences with mathematics.

DeVaney (2010) conducted a study with 27 on-campus students (5 males and 22 females) and 93 online students (18 males and 75 females). The study compared the levels of statistics anxiety and attitudes toward statistics revealed by graduate students. Statistics anxiety was measured by using three sub-scales from STARS

(*Interpretation Anxiety, Fear of Asking for Help* and *Test and Class Anxiety*), administered at the beginning and end of a statistics course. Attitude toward statistics was measured by the Survey of Attitude Toward Statistics (SATS-28) at the beginning and end of the 10-week course. The SATS-28 contains 28 statements related to statistics, using a 7-point scale ranging from Strongly Disagree (1) to Strongly Agree (7) for all items, and contains four sub-scales, namely (a) Affect, (b) Cognitive, (c) Value, and (d) Difficulty.

In a similar study, Perepiczka et al. (2011) found a negative correlation between statistical anxiety and self-efficacy in the learning of statistics *(r=-0.679)*, a positive correlation between self-efficacy to learn statistics and attitude towards statistics *(r=0.708)*, and a negative correlation between statistics anxiety and attitude towards statistics (*r= -0.832*). The STARS was used to measure statistics anxiety, and attitude toward statistics was measured by the Attitude Toward Statistics (ATS) scale (Shultz and Koshino, 1998). ATS is a 29-item, 5 point Likert scale ranging from Strongly Disagree to Strongly Agree. Self-efficacy in the learning of statistics was measured by the Self-Efficacy to Learn Statistics (SELS) scale (Finney and Schraw, 2003). The SELS measures confidence in one's ability to learn necessary statistics while in a statistics course. It contains 14 specific tasks rated on a 6-point response scale ranging from 1 (No Confidence) to 6 (Complete Confidence).

The results showed a statistically significant relationship between self-efficacy to learn statistics, statistics anxiety and attitude towards statistics. Statistics anxiety and attitude towards statistics were statistically significant predictors of self-efficacy to learn statistics and accounted for 3% and 7% of the variance, respectively. Furthermore, Dempster and McCorry (2009) state that attitude towards statistics and prior experience of mathematics and statistics are good and important predictors of statistics performance at undergraduate level. Mills (2004) also concluded that students who feel confident with materials in an introductory statistics class exhibit mostly positive attitudes toward statistics.

2.10 Statistics Anxiety and Gender Differences

Gender is one of the most widely investigated environmental variables in statistics anxiety research. Studies have found that there are significant differences within statistics anxiety measures by gender (Onwuegbuzie et al., 1999; Vahedi et al., 2011; Koh and Zawi, 2014). Some studies have found that female students have higher statistics anxiety compared to male students (Benson, 1989; Zeidner, 1991; Papanastasiou and Zembylas, 2008; Vahedi et al., 2011). However, other researchers had different findings. Cruise and Wilkins (1980), Onwuegbuzie (1999), Onwuegbuzie (2004) and Lacasse and Chiocchio (2005) did not find any conclusive association between gender and statistical anxiety. Koh and Zawi (2014), moreover, found that gender was associated with self-perception of the ability to perform in statistics. Several studies mention that female students have been reported to encounter more difficulties in quantitative areas (Zeidner, 1991; Vahedi et al., 2011).

Baharun and Porter (2009) found that males have significantly more confidence in their understanding of statistics topics (e.g determining probabilities from tables, using regression output and writing meaningful paragraphs about variables) than females. In addition, Vahedi et al. (2011) used the Statistics Anxiety Measure (SAM) and concluded that, "...female students reported a more negative attitude towards statistics classes than male students." SAM is a 43-item rating scale with sub-scales rated on a 7-point scale ranging from 1= Strongly Disagree to 7= Strongly Agree. SAM comprises of five discrete sub-scales: Anxiety, Performance, Attitude toward Class, Attitude toward Mathematics, and Fearful Behaviour.

Eduljee and LeBourdais (2015) conducted an empirical study examining gender differences in statistics anxiety. The sample included 156 undergraduate college students (48 males and 107 females) from a liberal arts college in the United States. In this study, three sub-scales of the STARS were used. No gender differences were obtained for the Worth of Statistics and Computation Self-Concept sub-scales. However, females had greater anxiety on the Test and Class Anxiety sub-scale than males. No significant correlations were found between statistics anxiety and course grades for males, while, for females there were significant correlations between Worth of Statistics and course grades and Computation Self-Concept and course grades.

2.11 Treatments to Reduce Statistics Anxiety

Researchers have suggested remedies that may reduce statistics anxiety. Dillon (1982) argues that students' statistics anxiety can be lowered by encouraging them to talk about their fears, and suggests ways that they can cope with their statistics anxiety (e.g. discussion groups, consultations with their teachers, tutorials and assignments). Schacht and Stewart (1990) agree that gathering data from the students themselves and having students perform simple calculations (calculations of mean, variances, mode, standard deviation, etc.) may reduce anxiety levels and increase motivation to become involved in the class.

Perepiczka et al. (2011) state that "decreasing anxiety among graduate students is vital to developing high levels of self-efficacy towards statistics." Engaging students in research throughout their graduate studies exposes them to statistics, which increases students' confidence when faced with taking a statistics course. Also, inserting research and statistics into the curriculum of every graduate course exposes graduate students to the terminology and the role of statistics in their development as professionals. Other ways to decrease statistics anxiety include language and experience. Allowing graduate students to learn what is being said in a statistics course through a weekly vocabulary test can also be one example of decreasing students' anxiety.

Lectures teaching statistics can play a key role by positively impacting their students' attitude toward statistics (providing a safe space for students to talk about their challenges, and celebrating their small successes can also be a tool to enhance a positive attitude and building confidence). Improving their attitude towards statistics can help graduate students re-frame their negative views toward statistics. Quinn (2006) report that "Giving students the opportunity to discuss the statistics tests through their journal writing, group presentations and SPSS discussions allowed them to immerse themselves further into understanding the statistical tests, thus potentially increasing their comfort with the material and further reducing anxiety." Eduljee and LeBourdais (2015) state that teaching methods that demonstrate various statistical techniques decrease statistics anxiety.

Schau (2003) suggested other techniques on how to treat statistics anxiety among students: 1) encouraging students who have debilitating anxiety or lack of confidence to seek assistance, 2) by bringing a positive attitude to the course, 3) stressing that a statistics course is not a mathematics course, 4) teaching that statistics is valuable, 5) recognising students' positive and negative attitudes by using humor to teach statistics, and 6) assessing student attitudes by having classroom discussions about attitudes. Firmin and Proemmel (2011) claim that "class time is finite, and focusing on becoming intelligent consumers of statistics and the principle behind the calculations can reduce anxiety and produce students who actually use the material from their statistical courses in the future." They also discussed strategies that can be used to reduce students' statistics anxiety in their classes:

- Spending time helping students see connections between learning statistics and their professional futures.
- Making statistics more interesting by using technology to enhance students' experience.
- Using a conceptual approach rather than a computational approach.
- Using classroom exercise and demonstrations and holding study sessions and tutorials to reduce students' statistics anxiety.

Chew and Dillon (2014) report that the learning system should be in a place to allow for anonymous questions because some students experience anxiety related to

Fear of Asking for Help and *Fear of Statistics Teachers*. For example, the Blackboard Learning System allows instructors to set up fora and/or collate questions to address in class. The emphasis on mathematics in a statistics course should also be reduced. Although formulae and calculations might help students understand statistics, these might aggravate the situation because students have to deal with mathematics anxiety in addition to statistics anxiety.

2.12 Conclusion

This chapter presents an overview of information that is essential to the understanding of the implications of statistics anxiety on students' performance. A brief overview of several implications of statistics anxiety over students' performance in statistics education are given. In addition to the direct effects of statistics anxiety on performance, this study is also interested in the effects of statistics anxiety that indirectly affect performance. These could include psychological symptoms, attitude, gender differences, and the degree to which these are related to students' disposition and experiences.

The literature review may assist in providing an understanding of the role and impact of statistics anxiety in higher education. In addition, the literature review may assist in providing educators with clear distinctions between statistics anxiety and mathematics anxiety since many people incorrectly assume that statistics anxiety has the same construct as mathematics anxiety. The dimensions of statistics anxiety and mathematics anxiety similarities are also made clear.

Tools and instruments used to assess statistics anxiety were discussed. They are the STARS, 40-item Statistics Anxiety Inventory, 10-item Statistics Anxiety Scale, 36-item unnamed instrument, 44-item Statistics Anxiety Measure and 24-item Statistics Anxiety Scale. Clear distinctions between all six sub-scales of STARS are indicated. According to the literature, STARS is the most popular instrument, showing a strong content validity and reliability.

The literature revealed that statistics has always been an anxiety provoking subject for students. According to Onwuegbuzie and Wilson (2003), more or less 80% of science students experience a high degree of statistics anxiety. In addition, other researchers agree that for many university students, statistics is one of the most anxiety-inducing courses in their curriculum (Caine et al., 1978; Lundgren and Fawcett, 1980; Blalock Jr, 1987; Zeidner, 1991).

Statistics anxiety has an effect on performance, either negative or positive. In general, a consistent negative relationship has been described between statistics anxiety and performance in various studies (Onwuegbuzie and Seaman, 1995; Keeley et al., 2008; Hanna and Dempster, 2009). Literature reveals that students with high statistics anxiety tend to fail statistics courses. In other words, students who experience higher levels of statistics anxiety tend to have lower academic performances in a statistics course.

Attitude toward statistics have been conceptualised as a multidimensional construct which consists of two main factors: (a) Attitude towards Field and (b) Attitude toward Course (Wise, 1985). A consistently positive relationship was observed from the literature between attitude toward statistics and performance. Students with a positive attitude toward statistics therefore tend to perform better in a statistics course. Furthermore, Mji and Onwuegbuzie (2004) and Chew and Dillon (2014) reported that Attitude toward Course tends to have more significant relationships with statistics achievement than Attitude toward Field. The literature reveals that most researchers conceptualise attitudes as a purely affective construct (Gal and Ginsburg, 1994; Mills, 2004; Evans, 2007), while others conceptualise it as consisting of affective, cognitive, and behavioral components (Onwuegbuzie and Wilson, 2003; Pan and Tang, 2005; Malik, 2015).

Statistics anxiety can negatively affect students' performance and their overall psychological condition. The literature reveals some psychological symptoms observed in students expressing their concerns over statistics anxiety, such as *depression, frustration, panic* and *worry*, along with psychological signs of *headaches, muscle tension, perspiration* and *feeling sick*. Ali and Iqbal (2012) state that statistics anxiety can have drastic implications on students' performance. They can experience deterioration in their performance in a statistics class, and they can experience inadequate feelings along with low self-efficacy in activities related to statistics, leading to failing the course.

The literature indicates that several factors such as fear of mathematics, lack of connection to everyday life, pace of instruction and attitude contribute to statistics anxiety. Students who come into a statistics course already fearful and expecting negative results mostly report more statistics anxiety. Researchers indicate that statistics anxiety is rooted in dispositional factors, situational factors and environmental factors. Dispositional factors are individual traits that determine how a student will react in a stressful situation, and include mathematics self-concept, perfectionism and the need for approval, and emotional characteristics such as negative attitudes toward statistics. Situational factors are those that occur while a student is taking a statistics course, including positive feedback, instructional pace, rigidity and formality of the course, and the introduction of Greek symbols. Environmental factors are those experiences students had prior to taking the statistics class and include gender, age, ethnicity, prior studies, and previous mathematics or statistics experiences.

Regarding gender differences in statistics anxiety, the literature reveals that some researchers have found that female students experience greater levels of statistics anxiety than males. Other studies reported no gender difference in statistics anxiety.

The last part of this chapter discusses recommendations made by researchers regarding methods to reduce statistics anxiety. For example, Dillon (1982), Schacht and Stewart (1990), Schau (2003) and Perepiczka et al. (2011) suggest that teaching methods that demonstrate various statistical techniques decrease statistics anxiety. Other recommendations are spending time helping students to see the connection between learning statistics and their professional future, as well as using classroom exercises, demonstrations and holding study sessions and tutorials to reduce students' statistics anxiety. In addition, using a conceptual rather than a computational approach may reduce statistics anxiety.

What follows is a description of the methods used in the empirical study, and the analysis of the data that was collected in Chapters 3 and 4 respectively. The review of the conclusion, limitations and implications of this research will be presented in Chapter 5.

Chapter 3

Research Design and Methodology

3.1 Introduction

In Chapter 1, orientation and background of the study was presented, whilst the research problems, questions, aims and objectives were introduced. In Chapter 2, a literature review was conducted to highlight contemporary perspectives on the impact of statistics anxiety on academic performance as well as the effects of statistics anxiety that indirectly affect performance. This chapter contains a description of the research design and the methodology applied to the empirical investigation implemented in this study. The theory and explanation of the design and selected methods will be discussed. In addition, the statistical techniques used to analyse the data will be presented.

Against the background to the problem in Chapter 1, the following research questions guide the empirical study:

- *What is the effect of statistics anxiety, attitude toward statistics and mathematics self-concept on students' performance in an introductory statistics course?*
- *Is there a relationship between statistics anxiety, attitude toward statistics and mathematics self-concept?*
- *Are there any gender differences regarding statistics anxiety, attitude toward*

statistics, mathematics self-concept and performance?

- *Do students become less or more anxious over the course of the semester?*
- *Do students' attitudes toward statistics and mathematics self-concept change over the course of the semester?*

The overall aim of the empirical study, as stated in Chapter 1, is to examine the association of statistics anxiety, attitude toward statistics and mathematics self-concept with regard to performance in an introductory statistics course. Specifically, the aim is to determine whether or not statistics anxiety affect students' performance. In addition, the study aims to determine whether statistics anxiety differs by gender and to investigate the experiences and opinions of students regarding statistics anxiety.

The above aims were realised by pursuing Objective 1 and Objective 2 as indicated in Chapter 1, namely:

1. To statistically investigate (i) the effect of statistics anxiety on students' performance, (ii) the relationship between attitude toward statistics and statistics anxiety, (iii) the relationship between attitude toward statistics and performance, (iv) the relationship between mathematics self-concept and statistics anxiety, (v) the relationship between mathematics self-concept and performance, (vi) gender differences regarding statistics anxiety, attitude toward statistics and mathematics self-concept and (vii) the trend of statistics anxiety, attitude toward statistics and mathematics self-concept over the course of the semester.
2. To gather qualitative information on the experiences and opinions of students regarding statistics anxiety and their attitude toward statistics by means of interviews.

For the purpose of the empirical study, the research questions were formulated as the following null and alternative hypotheses:

H_0a: No association between student performance and any of the following: statistics anxiety, attitude toward statistics and mathematics self-concept.
H_1a: There is association between student performance and at least one of the following: statistics anxiety, attitude toward statistics and mathematics self-concept.

H_0b: Statistics anxiety, attitude toward statistics, mathematics self-concept and performance between males and females do not differ.
H_1b: Statistics anxiety, attitude toward statistics, mathematics self-concept and performance between males and females differ.

H_0c: Students' statistical anxiety, attitude toward statistics and mathematics self-concept remains the same during the course of the semester.
H_1c: Students' statistical anxiety, attitude toward statistics and mathematics self-concept changed during the course of the semester.

The chapter commences with an overview of the methods used, the identification of the variables, provides a more general description of the research design and provides a rationale for why certain methodological components were chosen. The remaining sections describe the participants involved in the study, the procedures used for sampling, the instruments that were used in the study, and outlines the methodology used to analyse the data. The final sections focus on validity and reliability issues encountered in the study, as well as some ethical considerations and limitations.

3.2 Overview of Methods Used

Questionnaires are widely used in survey research, observations, content analyses, and can also be used to collect information (De Vaus, 2002, p. 3). The current study will make use of a questionnaire to collect the information.

On the first day of class, students in an introductory business statistics class were informed of the nature of the study and asked if they would be willing to participate. It was made clear that participation was voluntary, and that their decision to participate would not affect their results in the course. The participants were assured of the confidentiality of the study, and were then given a questionnaire consisting of a statistics anxiety instrument, attitude toward statistics instrument and a mathematics self-concept instrument. The survey was anonymous; students' names were not linked to their responses. Anonymity was thought to increase the level of honesty in responses. To ensure confidentiality, students identified themselves on the questionnaire through the use of a code name known only to them and the researcher.

There were three administrations of the questionnaires. The first stage of the distribution of questionnaires was in February 2016 before the formal classes started so as to test the statistics anxiety, attitude toward statistics and mathematics self-concept of students before lectures commenced. The second distribution of questionnaires was March 2016 after Test 1 was written, to monitor the implications of Test 1 on students' anxiety, attitude toward statistics and mathematics self-concept. The last and final stage of the distribution of the questionnaires was in May 2016 after Test 2 was written. The researcher also conducted face to face, semi-structured interviews after the examination was written to elaborate on the quantitative data and to generate qualitative data on detailed views, opinions and experiences regarding statistics anxiety, attitude toward statistics and mathematics self-concept.

3.3 Identification of variables

The variables of a study are the phenomena or factors that are being researched. The factor or phenomenon studied is not constant but is subject to variation, hence its name (Colman, 2001; Fraenkel and Wallen, 2008). Furthermore, a variable is a characteristic or an attribute of the study object and is a property that takes on different values (Welman et al., 2005, p. 16).

3.3.1 The dependent variable

(Fraenkel and Wallen, 2008, p. 42) state that "... the dependent variable depends on what the independent variable does to it, and how it affects it." The dependent variable is what you measure in the experiment and what is affected during the experiment. The dependent variable responds to the independent variable, *i.e.*, a change in the independent variable is what causes the change in the dependent varaible (Welman et al., 2005, p. 16).

The dependent variable in this study is performance in an introductory business statistics course, as the main question of interest is whether statistics anxiety, attitude toward statistics and mathematics self-concept has an effect on student performance.

3.3.2 The independent variable

The independent variable is the variable in an experiment that is being changed or manipulated and is presumed to affect at least one other variable (Welman et al., 2005, p. 16). Fraenkel and Wallen (2008, p. 42) state that "... an independent variable is presumed to affect (at least partly cause) or somehow influence at least one other variable. The variable that the independent variable is presumed to affect is called a dependent variable".

For the purpose of this study the independent variables are statistics anxiety, attitude toward statistics, mathematics self-concept and anxiety sub-scales.

3.3.3 The confounding variables

Confounding variables are also known as extraneous variables, third variables or nuisance variables. These variables are independent variables that have not been controlled and that could possibly influence the dependent variable (Viljoen, 2007; Fraenkel and Wallen, 2008). Thus, a confounding variable is a variable that cannot be controlled for by the researcher. Viljoen (2007, p. 16) gives a clear description of confounding variables by stating: "Confounding variables are variables that may influence our results but which are not a part of our study or are not what we are interested in". The confounding variables in this study were students' age and students' class attendance.

3.4 Research Design and Methodology

The following sections describe the research design and methodology employed in the empirical study. A research design should provide a plan that specifies how the research is going to be executed in such a way that it answers the research questions (Blanche et al., 2006).

A starting point in formulating this plan according to Blanche et al. (2006) is to decide on the classification of the basic design. First one needs to understand the distinction between experimental and non-experimental research. Kerlinger (1986, p. 348) defines non-experimental research as the systematic empirical inquiry in which the scientist does not have direct control of independent variables because their manifestation has already occurred or because they are inherently not manipulable. Bernard and Whitley (2002) explains that experimental research seeks to obtain answers by manipulating a condition, in other words by introducing some change into a situation. The purpose of experimental research is "... to investigate cause and effect relationships between manipulated conditions and measured outcomes (McMillan, 2001, p. 32). On the other hand, non-experimental designs are used when the researcher wants to describe phenomena and possible relationships/ differences between them, while no direct manipulation (control) of conditions takes place (McMillan, 2001, p. 33). Each of the experimental and non-experimental categories are characterised by different types of designs.

Non-experimental research designs can be classified as qualitative or quantitative research. McMillan (2001, p. 15) simplify the description of quantitative research as empirical research in which the data are in the form of numbers. McMillan (2001, p. 13) further describe quantitative research as a hypothetic-deductive approach. It makes deductions from theory and therefore identifies a hypothesis. The hypothesis is then tested by means of the data to confirm, reject, or modify the theory. A typical type of research study that employs quantitative research would be an experiment or a survey study (Ivankova et al., 2007). According to Ivankova et al. (2007), the goal of quantitative research is to rely on numerical data to test the relationship between the variables.

For the purpose of this research, a non-experimental research design was used. The researcher used numerical data (test marks, examination marks and questionnaire results) to test the relationship between variables as well as to test the formulated hypotheses (see section 3.1). Some advantages of quantitative research are that the researcher tends to remain objectively separated from the subject matter, that the use of numbers allows for greater precision in reporting results, and that quantitative research permits the use of powerful methods of mathematical analysis (Neill, 2007). The quantitative paradigm was considered appropriate for this study as the research involved the collection of numerical data and various statistical methods were used to analyse the data.

3.4.1 Overview of Research Methods

The research in this study was conducted using a quantitative non-experimental longitudinal design due to the nature of the research hypotheses. This study was conducted using qualitative semi-structured interviews. According to Welman et al. (2005), longitudinal design is relevant when we want to investigate changes due to the passage of time. This time period may extend from weeks to years. There are three types of longitudinal design, namely, *panel designs, cohort designs* and *trend designs*.

In this study a cohort design was used. In a cohort design study, the researcher uses an intact group, such as the business statistics class included in this study. Such a group is then followed over a period of time and measured in respect of the same dependent variable. Cohort studies resemble intervention studies in that people are selected on the basis of their exposure status and then followed up in time. In cohort study, the allocation to the study groups is not under the direct control of the researcher.

Quantitative research searches for relationships between variables and it may also explain the relationships between different variables (Fraenkel and Wallen, 2008, p. 15). The study was non-experimental because there was no randomisation of the sample and no attempt was made to change behaviour in the study. Many variables were included in the design to attempt a prediction of the interdependence between multiple independent variables and the dependent variable, namely performance in the business statistics course. Because non-experimental methods were used instead of random sampling, the results cannot be generalised to the population. However, inferences from the study's results can be made and the applicability to a larger population can be hypothesised.

Figure 3.1 presents a summary of the thought process followed to arrive at the classification of the design.

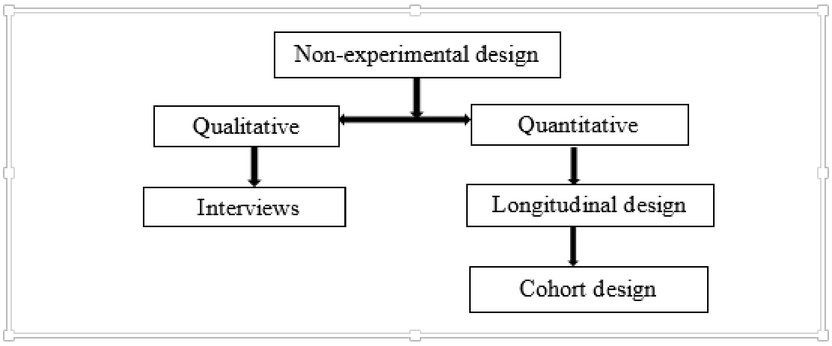


Figure 3.1: The Basic Research Design for the Current Study.

The study also followed a descriptive survey design as quantitative data were collected by means of a standardised research instrument in the form of a questionnaire. According to Punch (2003, p. 23-24) there are seven major components to consider when conducting surveys, including:

- The objective of the survey
- The research questions to be answered through the survey.
- *The questionnaire to collect information.*
- *The sample of the target population.*
- *The data collection strategy.*
- *The data analysis strategy.*
- The report on the survey.

The research objectives and research questions components were presented in Chapter 1 and the report will be presented in Chapters 4 and 5. The main focus of the current chapter is therefore on the questionnaire, the sample, data collection strategy, and the data analysis strategy (indicated in italics above). In addition, the study included a qualitative instrumental case study design through semi-structured interviews. However, less priority was given to this qualitative data; qualitative inferences were used only to augment the quantitative inferences.

3.4.2 Population and sampling

Different aspects relating to the population and sampling for the study are addressed in this section, including information on the location of the study, participant selection and the sampling methods employed.

3.4.2.1 Location of study

This study was conducted at the University of the Free State (UFS), Bloemfontein, South Africa. The University is a multicultural institution with more than 30000 students in nine different faculties. These faculties offer a wide range of undergraduate and postgraduate courses to South African students, but also to students from more than fifty countries around the globe, although most international students are from neighbouring and other African countries.

3.4.2.2 Participant selection

The population refers to the group that is relevant to the researcher's study and to whom the findings of the study would be generalised (Fraenkel and Wallen, 2008, p. 91). Bless et al. (2006, p. 184) refer to the population as "...the complete set of events, people or things to which the research findings are to be applied." This group is also known as the target population. Under the term population, Fraenkel and Wallen (2008, p. 91) distinguish between the target population and the accessible population. The target population refers to the whole group that the researcher *would like to study* and to generalise the study to. The accessible population is that part of the target population that the researcher *was able to study*, because it is rarely possible to involve the whole target population in the research.

In this study a non-stochastic sampling method was used as the participants were selected on the basis of their availability (i.e. students were not randomly selected). First, convenience sampling was employed because the introductory statistics students were easily accessible (they studied at the researcher's own institution) and they were available at a given time (they attended lectures during specific time slots). According to Welman et al. (2005, p. 69-70), a convenience sample is chosen when it is not possible to access a wider population and when a homogeneous population is assumed.

The participants in this study were homogeneous in the sense that they were more or less of the same age, had the same mathematical background and were taught by the same lecturer throughout the course. Second, judgement sampling was employed according to the following criteria: (i) participants had to complete all three questionnaires during the course of the study and (ii) participants had to obtain a mark for both tests as well as an examination mark. The accessible population in this study comprised of 103 introductory business statistics students. For the purpose of conducting semi-structured interviews, 6 students were randomly selected from the initial sample of participants.

Figure 3.2 presents the sampling process for Participant selection in this study.

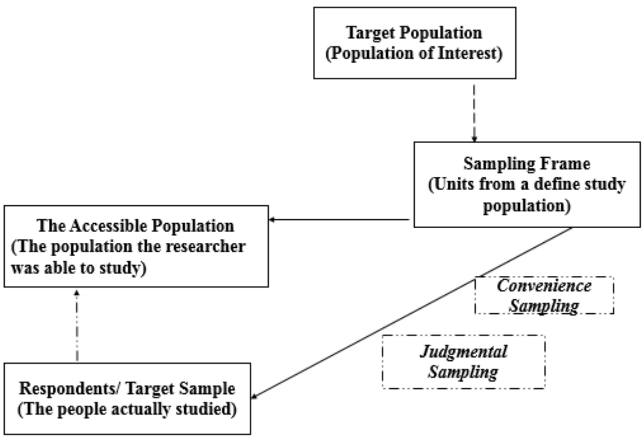


Figure 3.2: The Sampling Process for the Current Study.

3.4.3 Measuring instruments

For this study, Statistics Anxiety Rating Scale (STARS) instrument was used to collect quantitative data. The questionnaire included three sections. The first section was to measure students' anxiety toward statistics and included 11 Likert scale questions. The second section was to measure students' attitude toward statistics and consisted of 25 Likert scale questions. The third section measured students' mathematics self-concept and included 10 Likert scale questions. This section was added to the two sections of STARS and was obtained from Marsh and O'Neill (1984). All in all, the survey was made up of 46 Likert questions from the different sections. According to Welman et al. (2005, p. 156-157), the Likert scale is useful in measuring people's opinions and is easy to compile and complete. A four-point and five-point Likert scale was adopted in this study. The choice of the four-point scale was conducted in the third section (*Mathematics Self-Concept*) and was influenced by the desire to prevent respondents from being neutral. In contrast to the original STARS questionnaire, some questions were omitted from the current study as they were not relevant to first year students.

Likert scale questions such as the scales used in the current study are classified as interval scales. While these are strictly speaking ordinal in nature, they are often considered as interval scales by researchers to enable the calculation of means and parametric significance testing.

A summary of the questionnaire is given as follows:

- In Section A, participants responded to statements about anxiety toward statistics. Answers in Likert scale questions were coded as: 1-No anxiety, 2-Partial anxiety, 3-Neutral, 4-Anxiety, and 5-Very much anxiety.
- In Section B, participants responded to statements about their attitude toward statistics. Answers were coded in Likert scale as: 1-Strongly disagree, 2-Disagree, 3-Neutral, 4-Agree, and 5-Strongly agree.

- In Section C, participants responded to statements about their mathematics self-concept. Answers were coded in Likert scale as: 1-Never, 2-Sometimes, 3-Most of the time, and 4-Always.

A set of open-ended questions were developed for interviews to allow sub-sampled students to share their experiences regarding statistics anxiety and attitude toward statistics (see Appendix B). The researcher audio-taped students and used hand-written notes to support the recordings. This helped the researcher with the transcriptions for analysis purpose.

Two semester tests were written in the introductory business statistics course. Both tests consisted of two sections. Section A consisted of multiple-choice questions (20 marks) and Section B consisted of standard, worded problems (40 marks). Several questions asked students to comment on, determine, explain, or interpret their results in words.

The following topics were covered in Test 1.

- Introduction to statistics
- Measures of location and dispersion
- Basic probability

The following topics were covered in Test 2

- Elementary interest calculations
- Probability distribution
- Index numbers
- Introduction to sampling distribution

As mentioned before, students' anxiety was also measured with performance in their examination. The examination counted 100 marks and consisted of two sections:

Section A consisted of multiple-choice questions (40 marks) and Section B consisted of short answer questions and "story" problems (60 marks).

3.4.4 Data collection

The main source of data was the researcher's records of the STARS instrument results and student performance in the course.

The test and examination marks were obtained from the university's student mark database and were recorded for each student as a percentage in a SPSS and an Excel spreadsheet. For Section A and Section B of the STARS instrument, sub-scale scores were obtained by calculating the mean response of the items composing the sub-scale. Results were recorded in the same SPSS and Excel spreadsheet mentioned above. Higher sub-scale scores corresponded to higher statistics anxiety and more negative attitudes toward statistics.

In Section C of the questionnaire (measuring mathematics self-concept), some statements were negatively worded and required reverse coding before the data could be recorded in the SPSS and Excel spreadsheet. Again, the mean response of the items were recorded. Higher scores corresponded to a higher mathematical self-concept.

Students were also required to indicate their gender on the STARS instrument, and this data was recorded as well.

Once the quantitative data had been captured, six students were randomly selected for follow-up face-to-face, semi-structured interviews. Each student was interviewed individually and spent approximately 30-45 minutes in the interview. All the interviews were conducted within a week's period and were tape-recorded with the approval of the interviewees. As mentioned before, field notes were taken during the interviews to support the recordings.

3.5 Quantitative data

In quantitative research the researcher makes decisions about what to study, what specific narrow questions to address, which numeric data to collect from participants, and which statistics to collect from the numeric data in order to answer the chosen questions. The researcher performs the investigation in an objective and unbiased manner (Creswell, 2002). In this study the quantitative data were analysed with the aid of the SPSS and SAS software.

3.5.1 Data analysis strategy

The analyses of data refers to the categorising, ordering, manipulating and summarising of data to obtain answers to research questions and to test research hypotheses (Kerlinger, 1986, p. 125). Statistics can be grouped into two main categories, namely descriptive and inferential statistics (Clayton, 1984). Descriptive statistics consists of the collection, organisation, summarisation and presentation of data, while inferential statistics consists of generalising from samples to population, performing estimations and hypothesis tests, determining relationships among variables, and making predictions. Both these types of statistics were calculated and used to answer the research questions.

3.5.1.1 Statistical significance

In order to test for significance, it is necessary to report both the effect size and the statistical (p) value. The larger the size of the total number of observations (N), then the larger the value of the test statistic (etc. t, F, χ^2) will be and hence the smaller the p-value. Inferential statistics are mostly said to be significant at $p<=0.05$ levels, where it is being reported that the probability of a Type I error is less than 5% (Rosenthal and Rosnow, 1991).

It is imperative to note that errors of rejecting the null hypothesis were considered in this research. Research tends to accept that when p<=0.05, then acceptable levels of significance have been achieved. Care should be taken not to make Type I (risk of false H_0 rejection) or Type II (risk of falsely failing to reject H_0) errors. According to Rosenthal and Rosnow (1991), to reduce the risk of these errors, the size of the study should be considered when determining significance.

Inferential statistics are therefore used to calculate the probability of obtaining the observed data if the null hypothesis is true. If the probability is small it is unlikely that the null hypothesis is true and one could therefore conclude that the null hypothesis is false. There is always a chance that the researcher might be wrong in his or her decision, using the probability guidelines. If the researcher rejects the null hypothesis and concludes that the population means are not equal, when in fact they are in the real population, then a Type I error was made. If the significance value is set at 0.05, it indicates that this type of error will occur 5% of the time (Graziano and Raulin, 1989, p. 104).

The most frequently used level of statistical significance is 0.05. According to Graziano and Raulin (1989), this is not a "magical figure" but rather one of convention. For some studies on particular controversial topics or where making a Type I error could have critical consequences, a more strict level could be chosen. For the purpose of this study however, the significance level of 0.05 is considered adequate.

3.5.1.2 P-value

The probability of drawing a t-statistic (or z-statistic) as extreme as the one actually observed, under the assumption that the errors are normally distributed, or that the estimated coefficient are asymptotically and normally distributed will be used. This probability is also known as the p-value. A p-value of lower than the significance level is taken as evidence to reject the null hypothesis of a zero coefficient.

According to Westfall and Young (1993), the p-value is defined as the probability, under the null hypothesis H_0, of obtaining a result equal to or more extreme than what was actually observed. The "more extreme than what was actually observed" can mean $X \geq x$ (right-tail event) or $X \leq x$ (left-tail event) or the "smaller" of $X \leq x$ and $X \geq x$ (double-tailed event). Thus, the p-value is given by:

- $Pr(X \geq x|H)$ for right tail event,
- $Pr(X \leq x|H)$ for left tail event,
- 2min $[Pr(X \leq x|H), Pr(X \geq x|H)]$ for double tail event.

The p-value is the probability of obtaining the observed sample results (or a more extreme results) when the null hypothesis is actually true. According to Hochberg (1988), if the p-value is very small, usually less than or equal to a threshold value previously chosen called the *significance level* (traditional 5% or 1%), it suggests that the observed data is consistent with the assumption that the null hypothesis is true, and thus that hypothesis must be rejected and the alternative hypothesis accepted as true.

Table 3.1: Interpretation of the p-value against level of significance

P-value >0.10	No evidence against null hypothesis. The data appear to be consistent with null hypothesis.
0.05 <P-value <0.10	Weak evidence against the null hypothesis in favor of the alternative hypothesis.
0.01 <P-value <0.05	Moderate evidence against the null hypothesis in favor of the alternative hypothesis.
0.001 <P-value <0.01	Strong evidence against the null hypothesis in favor of the alternative hypothesis.
P <0.001	Very strong evidence against the null hypothesis in favor of the alternative hypothesis .

3.5.1.3 Two-sample t-test

The test is used for testing the value of the difference between two population means. The measurement of one sample has no effect on the values of the other sample, therefore, the samples are independent (Malhotra and Malhotra, 2012).

To test for equality of means for two independent samples,
The null hypothesis is stated as:

$$H_0 : \mu_1 = \mu_2, \tag{3.1}$$

Against the alternative hypothesis as

$$H_1 : \mu_1 \neq \mu_2,$$

Two populations are sampled, and the means and the variances computed based on sample of sizes n_1 and n_2. If both populations are found to have the same variance, a pooled estimate is computed from the two sample variances and a pooled variance estimate is computed.

Assumptions of Two-sample t-test

- The data are continuous.
- The data follow the normal probability distribution.
- The variances of the two populations are equal.
- The two samples are independent.
- Both samples are simple random samples from their respective populations. Each individual in the population has equal probability of being selected in the sample.

3.5.1.4 t-statistic

The t-statistic allows researchers to use sample data to test hypotheses about an unknown population mean. Thus, the t-statistic can be used to test hypotheses about a *completely unknown* population; that is, both μ and σ unknown, and the only available information about the population comes from the sample. According to Malhotra and Malhotra (2012), the t-statistic is a measure of how extreme a statistical estimate is. One computes this statistic by subtracting the hypothesized value from the statistical estimate and then dividing by the estimated standard error. In most cases, but not all situations, the hypothesized value would be zero. The sample mean is estimated and its variance is also estimated as:

$$s_{\bar{X}} = \frac{s}{\sqrt{n}}, \tag{3.2}$$

Thus test statistic,

$$t = \frac{\bar{x} - \mu_0}{s_{\bar{X}}}, \tag{3.3}$$

is said to have a t-distribution with $n-1$ degrees of freedom. μ_0 is the hypothesised population mean. The above test is used to test the null hypothesis:

$$H_0 : \mu = \mu_0, \tag{3.4}$$

3.5.2 Descriptive statistics

The purpose of descriptive statistics is to arrange, summarise and present data in such a way to make the data meaningful and to extract and use the data meaningfully (Creswell, 2002). Descriptive statistics were used in this study to report on the data gathered. Included in these statistics were the mean and standard deviations. The mean is the average of all the values in each data set. The standard deviation is an estimate of the average distance each score is from the mean (Malhotra and Malhotra, 2012).

3.5.3 Test of normality

Assessing the assumption of normality is required by most statistical procedures. Parametric statistical analysis is one of the best examples to show the vital role of assessing the normality assumption. Parametric statistical techniques assumes a certain distribution of the data, usually the normal distribution. If the assumption of normality is violated, interpretations and inferences are mostly not valid. Therefore it is important to check for this assumption before proceeding with any relevant statistical analysis.

Gross violation of normality of residuals compromises the estimation of regression coefficients. Sometimes the error distribution is skewed by the presence of a few large outliers since parameter estimation is based on the minimisation of squared error. A few extreme observations can exert a disproportionate influence on parameter estimation. There are at least two approaches for test of normality assumption. The more formal approach is to conduct a statistical test of the assumption of normality. In this study, the statistical tests used are Kolmogorov-Smirnov, Shapiro-Wilk test, skewness and kurtosis. Graphical methods were also used to assess normality assumption in this study. The graphical approach used to test normality was quantile-quantile (Q-Q) plots.

3.5.3.1 Kolmogorov-Smirnov

The Kolmogorov-Smirnov test is a non-parametric test that allows one to test normality. It was first derived by Kolmogorov (1933) and later modified and proposed as a test by Smirnov (1948). The test statistic is

$$D = sup_x|F_n(X) - F(X, \mu, \sigma)|, \tag{3.5}$$

where, $F(X, \mu, \sigma)$ is the theoretical cumulative distribution function of the normal distribution function and $F_n(X)$ is the empirical distribution function of the data. If it gives large values of D then it indicates the data are not normal. When population parameters (μ and σ) are unknown then sample estimates are used instead of parameter values.

3.5.3.2 Shapiro-Wilk test

The Shapiro-Wilk denoted W, is the ratio of the best estimator of the variance to the usual corrected sum of squares estimator of the variance. According to Shapiro and Wilk (1965), The statistic is positive and less than or equal to one. If the statistic is close to one or the resulting p-value is above 0.05 then Shapiro-Wilks indicates normality. The W statistic requires that the sample size is greater than or equal to 7 and less than or equal to 2000. The Shapiro-Wilk test is one of the most popular tests for normality assumption diagnostics which has good properties and it is based on correlation within given observations and associated normal scores. The Shapiro-Wilk test statistic is

$$W = \frac{(\Sigma a_i y_i)^2}{\Sigma(y - \bar{y})^2}, \tag{3.6}$$

where,
y_i is the ith order statistics,
$a_i = (a_1, ..., a_n)$ is the ith expected value of normalised ordered statistics,
W is location and scale invariate and is always less than or equal to 1,
$\bar{y}$ is the sample mean.

3.5.3.3 Skewness and Kurtosis

Skewness and kurtosis are based on the empirical data. The statistical methods used to test normality compare empirical data with a theoretical distribution. Pearson (1895) initiated the effort of developing techniques to detect departures from normality by working on the skewness and kurtosis coefficients. According to Pearson (1895) skewness is asymmetric in a statistical distribution, in which the curve appears distorted either to the left or to the right. More researchers stated that skewness can be quantified to define the extent to which a distribution differs from a normal distribution. A common "rule of thumb" test for normality is to run descriptive statistics to get skewness and kurtosis, then divide these by their standard errors. Skewness should be within [-1.96 , +1.96] range when the data are normally distributed.

According to Pearson (1895), kurtosis is a measure of the "tailedness" or "peakedness" of the probability distribution of a real-valued random variable. The standard measure of kurtosis, initiated by Karl Pearson, is based on a scaled version of the fourth moment of the population. To conclude that the data are normally distributed is for the kurtosis to range between [-3 , +3].

$$Skewness = \frac{E[(X-\mu)^3]}{(E[(X-\mu)^2])^{3/2}} = \frac{\mu_3}{\sigma^3}, \tag{3.7}$$

where,
μ is the sample mean,
E is the expectation operator,
μ_3 is the third central moment.

$$Kurtosis = \frac{E[(X-\mu)^4]}{(E[(X-\mu)^2])^2} = \frac{\mu_4}{\sigma^4}, \tag{3.8}$$

where,

μ_4 is the fourth central moment ,

σ is the standard deviation.

3.5.3.4 Quantile-Quantile (Q-Q) plots

A Q-Q plot is a probability plot which is a graphical method for comparing two distributions by plotting their quantiles against each other. If the two distributions being compared are similar, the points in the Q-Q plot will approximately lie on the line $y = x$. If the distributions are linearly related, the points in the Q-Q plot will approximately lie on a line, but not necessarily on the line $y = x$. If the points follow the line $y = x$ they suggests that the data are normally distributed (Chambers et al., 1983).

3.5.4 Paired sample t-test

A paired sample t-test is a test for difference in the means of paired samples. To compute t-statistic for paired samples the paired difference variable (D) is created and its true mean (μ_D). The sample mean estimate ($\bar{D}$) is computed and the sample variance (S_D^2) is also calculated. Then the t-statistic is computed with degrees of freedom ($n - 1$), where n denotes the number of pairs.

The null hypothesis is stated as:

$$H_0 : \mu_D = 0, \tag{3.9}$$

Against the alternative hypothesis as

$$H_1 : \mu_D \neq 0,$$

The test statistic is

$$t = \frac{\bar{d} - \mu_D}{S_{\bar{D}}}, \tag{3.10}$$

Assumptions of paired samples t-test:

- The data are continuous (not discrete).
- The data, i.e the differences for the matched-pairs follow a normal probability distribution.
- The sample of pairs is a simple random sample from its population. Meaning each individual in the population has an equal chance of being selected in the sample.

3.5.5 Hotelling's T^2-test

The two-sample Hotelling's T^2-test is the multivariate extension of the common two-group student's t-test. In a t-test, differences in the mean response between two populations are studied. According to Rencher (2003), T^2 is used when the number of dependent variables are more than one, although it can be used when there is only one dependent variable. The null hypothesis is stated in a way that the group means for all dependent variables are equal.

Morrison (1998) state that Hotelling's T^2-test makes the usual assumptions of equal variances and normally distributed residuals. Preliminary tests are provided that allow these assumptions to be evaluated. Morrison (1998) noted that randomisation tests are provided that do not rely on these assumptions. These randomisation tests should be used whenever the researcher want exact results that do not rely on several assumptions.

According to Rencher (2003), the two-sample T^2-test is used to test the equality of the mean vectors of two populations. Suppose a set of p response variables $Y_1, Y_2, ..., Y_p$ is measured for each of two groups. Therefore, assume that population 1 is distributed as $N_p(\mu_1, \Sigma_1)$ and population 2 is distributed as $N_p(\mu_2, \Sigma_2)$, where $N_p(\mu, \Sigma)$ is the $p-$variable multivariate normal distribution with mean vector μ and covariance matrix σ.

Null hypothesis:

$$\mu_1 = \mu_2 \tag{3.11}$$

Test statistic:

$$T^2 = \tfrac{n_1 n_2}{n_1+n_2}(\bar{y_1} - \bar{y_2})' S_{pl}^{-1}(\bar{y_1} - \bar{y_2}), \tag{3.12}$$

where $\bar{y_1}$ and $\bar{y_2}$ are the two sample mean vectors, n_1 and n_2 are the two sample sizes, and S_{pl}^{-1} is the inverse of the pooled covariance matrix which is calculated by

$$S_{pl} = \frac{(n_1-1)S_1+(n_2-1)S_2}{n_1+n_2-2}, \tag{3.13}$$

where S_1 and S_2 are the estimated covariance matrices calculated from the two samples.

If additional assumption is made that $\Sigma_1 = \Sigma_2$, T^2 follows Hotelling's T^2 distribution when the null hypothesis is true. That is, $T^2 \sim T^2_{p,n_1+n_2-2}$. Then null hypothesis is rejected if $T^2 \geq T^2_{p,n_1+n_2-2}$. Therefore rejecting the null hypothesis concludes that at least one pair of the p sets of group response means are unequal.

3.5.6 Multivariate Analysis of Variance (MANOVA)

To investigate gender differences on statistics anxiety, attitude toward statistics and mathematics self-concept, multivariate analysis of variance (MANOVA) was utilised. Multivariate statistical analysis is concerned with data collected on several dimensions of the same individual. According to Johnson and Leone (1964), MANOVA refers to a well established technique that compares multivariate population means of several groups. The methods described in the univariate analysis of variance (ANOVA) can be extended to cases where more than one variate is measured on each individual. A multivariate hypothesis is constructed through a variance-covariance matrix for each line of the univariate analysis table. According to French et al. (2008), MANOVA is an ANOVA with several dependent variables. That is to say, MANOVA tests for the difference in two or more vectors of means. Carey (1998) stated that there are two major situations in which MANOVA is used.

The first is when there are several correlated dependent variables, and the researcher desires a single, overall statistic test on this variables instead of performing multiple individual tests. The second, and in some case, the more important one is to explore how independent variables influence some patterning of response on the dependent variables. The purpose of t-test is to assess the likelihood that the means of two groups are sampled from the same sampling distribution of means (French et al., 2008). When multiple individual t-tests are performed testing separation of dependent variable across correlated independent variable the significance level of simultaneous tests is artificially inflated.

The purpose of an ANOVA is to test whether the means of more than one groups are taken from the same sampling distribution. The multivariate equivalent of the t-test is *Hotelling's T^2-test*. Hotelling's T^2 tests whether the two vectors of means for the two groups are sampled from the same sampling distribution. According to Carey (1998), the purpose of MANOVA is to test whether the vectors of means for the two or more groups are sampled from the same sampling distribution. Just as Hotelling's T^2-test will provide a measure of the likelihood of picking two random vectors of means out of the same hat, MANOVA gives a measure of the overall likelihood of picking more than one random vectors of means out of the same hat.

Definition: one-way MANOVA

$$Y_{ij} = \mu + \tau_i + \epsilon_{ij} = \mu_i + \epsilon_{ij}, \tag{3.14}$$

$i = 1, 2, ..., k, \qquad j = 1, 2, ..., n_i,$

where:

Y_{ij} is a $p * 1$ outcome vector for the j^{th} subject from the i^{th} treatment.

$\mu = [\mu_1, \mu_2, ..., \mu_p]'$ is the overall population mean vector.

$\tau_i = [\tau_{i1}, \tau_{i2}, ..., \tau_{ip}]'$ is the i^{th} treatment effect vector for the p response variables.

ϵ_{ij} is the experimental error such that $\epsilon_{ij} \sim (0, \Sigma)$ with $\Sigma_{i=1}^{k} n_i \tau_i$=0.

Definition: two-way MANOVA

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk} = \mu_{ij} + \epsilon_{ijk}, \tag{3.15}$$

$i = 1, 2, ..., a, \qquad j = 1, 2, ..., b, \qquad k = 1, 2, ..., n,$

where:

α_i is the effect of the i^{th} level of A on each of the p variables in Y_{ijk}

β_j is the effect of the j_{th} level of B

γ_{ij} is the AB interaction effect.

According to Rencher (2003), side conditions are used, $\Sigma_i \alpha_i = \Sigma_j \beta_j = \Sigma_i \gamma_{ij} = \Sigma_j \gamma_{ij} = 0$ and assume the ϵ_{ijk} are independently distributed as $N_p(0, \Sigma)$.

Statistics to evaluate the MANOVA hypothesis:

- Wilks' lambda or U-statistic: It is often referred to as the multivariate F-test. It is preferred when basic requirements (sample size, no violations, approximately equal sized groups) are met.
- Roy's Test: It is mostly approprite when dependent variables are strongly interrelated on one dimension and it is strongly affected by violations of assumptions.
- Pillai and Lawley-Hotelling Test: Are more robust and preferred when sample size decreases, unequal groups, or when homogeneity of covariances is violated.

The statistic Wilks' lambda is the most common and traditional test in which there are more than two groups formed by the independent variables. It is a multivariate F-test, similar to the F-test in univariate ANOVA. The lower the Wilk's lambda, the greater the differences and the more the given effect contribute to the model. The t-test, Hotelling's Trace, and F-test are special cases of Wilks' lambda. For large samples, Wilks' lambda can be referred to a Chi-square. Everitt and Dunn (2001) state that, Wilks' lambda statistic can be transformed to a statistic which has approximately an F distribution.

MANOVA assesses the differences across combination of dependent variables, as this can construct a linear relationship only between dependent variables. The researcher will examine the data by assessing the following assumptions (Stevens, 2012; Carey, 1998):

- Multivariate normality: The dependent variables should be normally distributed within groups. The standard test for normality in this study are statistical approaches (Kolmogorov-Smirinov statistic, Shapiro-Wilk statistic, Skewness and Kurtosis). graphical approach (Q-Q plots) distinguish between systematic departures from normality when it shows up as a curve.

- Independence random sampling: commonly known as the *assumption of independence*. when conducting MANOVA the observations must be indepedent to one another. The indepedent variables are categorical in nature and the dependent variables are continuous variables. MANOVA assumes that homogeneity is present between the variables that are taken for covariates.

- Homogeneity of variances and covariances matrices: The population variances and covariances among the dependent variables are the same across all levels of the factor. That is, variances for each dependent variable are approximately equal in all groups plus covariances between pairs of dependent variables are approximately equal for all groups. The Box's M test statistic indicates heterogeneity when the test has statistical significance (p-value). The null hypothesis is that the variance between groups is equal. (French et al., 2008).

- Linearity: linear relationships are assumed between pairs of dependent variables, all pairs of covariates, and all dependent variable-covariate pairs in each cell. Therefore, if the relationships deviates from linearity, the power of the analysis will be compromised.

According to Rencher (2003), MANOVA is extremely sensitive to outliers. Failure to exclude outliers or transform the data could inflate either a Type I error or Type II error and give no indication as to which type of error is occurring in the analysis. Likewise, missing values in multivariate analysis become more problematic because of the complexity of the dependent variate.

3.5.6.1 Box's M test statistic

Box's M test is a statistic test which tests the homoscedasticity (equal variation of data) assumption in MANOVA such as that the all covariance is the same for any category. Box's M test is used to know the equality of covariance between the groups. The null hypothesis in MANOVA is that the observed covariance matrice of the dependent variable are equal across groups.

$H_0 : \Sigma_1 = \Sigma_2 = ... = \Sigma_p$. derived a test statistic based on the likelihood-ratio test. For moderate to small sample sizes, an F approximation is used to compute its significance.

3.5.7 Pearson's correlation coefficient

To investigate the properties of the anxiety sub-scales, correlation analysis was utilised on the sections of STARS and on the six anxiety sub-scales over the three administrations of questionnaire.

Correlation analysis is a statistical procedure that measures degree of association between two variables. The main result of correlation is called the **correlation coefficient** (***r***). If correlation coefficient is close to zero, it means there is no relationship between the variables. If correlation coefficient is positive, it means that as one variable increases the other variable increases. If correlation coefficient is negative it means that as one variable increases, the other variable decreases.

3.5.7.1 The Correlation of Data.

The correlation matrix refers to the symmetric array of numbers.

$$R = \begin{bmatrix} 1 & r_{12} & r_{13} & \cdots & r_{1p} \\ r_{21} & 1 & r_{23} & \cdots & r_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & r_{p3} & \cdots & 1 \end{bmatrix}$$

where

$$r_{jk} = \frac{S_{jk}}{S_j S_k} = \frac{\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)(x_{ik}-\bar{x}_k)}{\sqrt{\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)^2}\sqrt{\sum_{i=1}^{n}(x_{ik}-\bar{x}_k)^2}}, \tag{3.16}$$

Equation 3.18 is the Pearson correlation coefficient between variables $\boldsymbol{x}_j$ and $\boldsymbol{x}_k$.

3.5.7.2 Correlation Matrix from Data Matrix.

Correlation matrix can be calculated as:

$$\boldsymbol{R} = \frac{1}{n}\boldsymbol{X}_s^1\boldsymbol{X}_s, \tag{3.17}$$

where $\boldsymbol{X}_s = \boldsymbol{C}\boldsymbol{X}\boldsymbol{D}^{-1}$ with

- $\boldsymbol{C} = \boldsymbol{I}_n - n^{-1}\mathbf{1}_n\mathbf{1}_n^1$ denoting a centering matrix.
- $\boldsymbol{D}$ =diag $(s_1, ..., s_p)$ denoting a diagonal scaling matrix.

Therefore, the standardised matrix $\boldsymbol{X}_s$ has the form:

$$\boldsymbol{X}_s = \begin{bmatrix} (x_{11}-\bar{x}_1)/s_1 & (x_{12}-\bar{x}_2)/s_2 & \cdots & (x_{1p}-\bar{x}_p)/s_p \\ (x_{21}-\bar{x}_1)/s_1 & (x_{22}-\bar{x}_2)/s_2 & \cdots & (x_{2p}-\bar{x}_p)/s_p \\ \vdots & \vdots & \ddots & \vdots \\ (x_{n1}-\bar{x}_1)/s_1 & (x_{n2}-\bar{x}_2)/s_2 & \cdots & (x_{np}-\bar{x}_p)/s_p \end{bmatrix}$$

3.5.7.3 Correlation of a Variable with itself is one.

Assuming that $s_j^2 > 0$ for all $j \in$ (1,...,p), we have that

$$Corr(\boldsymbol{x}_j, \boldsymbol{x}_k) = \frac{S_{jk}}{S_j S_k} = \frac{\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)(x_{ik}-\bar{x}_k)}{\sqrt{\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)^2}\sqrt{\sum_{i=1}^{n}(x_{ik}-\bar{x}_k)^2}} = \begin{cases} 1 \quad if \quad j=k \\ r_{jk} \quad if \quad j \neq k \end{cases}, \tag{3.18}$$

if j=k then $r_{jk} = 1$, therefore:

- $tr(\boldsymbol{R}) = p$ where $tr(.)$ denotes the matrix trace function.
- $\sum_{i=1}^{n} \lambda_j = p$ where $(\lambda_1, ..., \lambda_p)$ are the eigenvalues of $\boldsymbol{R}$.

It can also be noted that the eigenvalues safisty:

- $\lambda_j = 0$ for at least one $j \in (1, ..., p)$ if $n < p$.
- $\lambda_j > 0 \ \ \forall \ \ j$ if columns of X are linearly independent.

Pearson's correlation coefficient was named after Karl Pearson, 1857-1936. According to Ezekiel and Fox (1959), correlation coefficient measures the strength of a linear relationship between two continuous variables and the absolute value of the coefficient measures how closely the variables are related.

Table 3.2: Interpretations of Pearson's correlation coefficients

Strength of Association	Positive Coefficient	Negative Coefficient
Very weak	0.00 to 0.19	0.00 to -0.19
Weak	0.20 to 0.39	-0.20 to -0.39
Moderate	0.40 to 0.59	-0.40 to -0.59
Strong	0.60 to 0.79	-0.60 to -0.79
Very strong	0.80 to 1.0	-0.80 to -1.0

The correlation matrix is a commonly used and easy to compute tool for detecting ***multicollinearity*** between predictor variables, however it has some limitations as a collinearity diagnostics. High correlation coefficient between a pair of predictor variables can indicate presence of multicollinearity problem, but the absence of high correlation coefficient does not always mean that there is no multicollinearity problem. The correlation matrix is not able to diagnose multicollinearity that involves three or more variables when there are no pairwise collinear relationships between the variables. This is due to the fact that three or more variable taken together can be collinear while there are no high pairwise correlations observed among them. The correlation matrix is also not able to show several collinear relationships that coexist in the set of data. Another shortfall of the correlation matrix as a collinearity diagnostic is lack of standard measure of how large should the correlation coefficient be to indicate collinearity.

3.5.8 Test for Multicollinearity

Multicollinearity is a statistical phenomenon in which there exists a perfect or exact relationship between the predictor variables, and it is difficult to come up with reliable estimates of their individual coefficients (Gujarati, 2004).

Multicollinearity is an unacceptably high level of inter-correlation among the independent variables, such that the effects of the independent variables cannot be separated under multicollinearity, estimates are unbiased but assessments of the relative strength of the explanatory variables and their joint effect are unreliable. Beta (β) weights and R-square (R^2) cannot be interpreted reliably even though predicted values are still the best estimates using the independent variables. High multicollinearity is signalled when high R-squared and significant F-tests of the model occur in combination with non-significant t-tests of coefficients.

According to Montgomery et al. (2015), the presence of multicollinearity has several serious effects on the ordinary least square estimates of regression coefficient such as high variance of coefficient that may reduce the precision of estimation, it can result in coefficients appearing to have the wrong sign, the parameter estimates and their standard errors become extremely sensitive to slight changes in the data points and it tends to inflate the estimated variance of predicted values. To test for the multicollinearity, Tolerance and Variance Inflation Factors (VIF) are considered.

3.5.8.1 Variance Inflation Factor

The variance inflation factor (VIF) is one of the commonly used measures of detecting the presence of multicollinearity in predictor variables. The VIF measures how much the variance of the estimated coefficients has increased over the case of no correlation among the explanatory variables. VIF are computed from the correlation matrix **C** of the predictor variables. The factors measure the quantity by which the variances of the estimated regression coefficients for correlated variables are inflated as compared to when the predictor variables are not correlated. Assuming that the predictor variables, which are columns of the data matrix **X** have been centered and scaled to unit length. The VIF are diagonal elements of the inverse C^{-1} of the correlation matrix **C**. The VIF of the j^{th} regression coefficient VIF_j, is defined as:

$$VIF_j = \frac{1}{1-R_j^2}, \quad 0 \leq R_j^2 \leq 1, \tag{3.19}$$

where R_j^2 is the coefficient of determination of the model that regresses the j^{th} predictor on all other predictors.

The name variance inflation factor was first introduced in 1960s by Marquardt (Belsley, 1991). The high value of VIF_j shows that the value of R_j^2 is close to 1. This is an indication of presence of multicollinearity, which leads to inflated variances of estimated coefficients. When variances of estimated coefficients get inflated they lead to small values of the t-statistic for individual coefficients hence causing insignificance, despite the overall model F-statistic being significant. If predictor variables are orthogonal, meaning that they are not linearly related, R_j^2 will be 0 and VIF_j

will be 1. A value of VIF that is greater than 5 is an indication of multicollinearity problems (Belsley, 1991). VIF values that 30 imply severe collinearity problems. However, values of VIF should be evaluated in relation to the overall fit of the model of interest (Freund and Wilson, 1998).

3.5.8.2 Tolerance

Often, tolerance is used together with VIF to detect the presence of near linear relationships among predictor variables. Tolerance measures the amount of variance in the j^{th} predictor variable X_j, which is not explained by other predictor variables. Tolerance can be expressed as the reciprocal of the VIF defined as:

$$\text{Tolerance} = \frac{1}{VIF_j} = 1 - R_j^2, \tag{3.20}$$

Where R_j^2 is as defined earlier. If there are linear relationships that involve X_j and other predictor variables, R_j^2 will be close to 1 and tolerance will be close to 0. This implies that almost all of the variability in X_j is explained by other predictor variables. The VIF and tolerance are inversely related. Values of tolerance that are less than or equal to 1, or equivalently values of VIF that are greater than or equal to 5 show that there may be problems of near dependencies among predictor variables.

Like the correlation matrix, the VIF and tolerance have a number of shortfalls. As it is the case with any measure based on correlation, large value of VIF and small values of tolerance are sign of multicollinearity problems. However, small values of VIF and large values of tolerance do not necessarily indicate the absence of multicollinearity problems. The VIF and tolerance are not able to diagnose several separate collinear relationships that exist simultaneously in the data matrix $\mathbf{X}$. Another shortfall of the VIF and tolerance is the lack of the well established methods of determining a meaningful cutoff point of large and small values of the two collinear diagnostics.

Rules of Thumb:

- *If any of the VIF values exceeds 10, it is an indication that the associated regression coefficients are poorly estimated because of multicollinearity (Montgomery et al., 2015).*
- *If one or more of the tolerance eigenvalues are small (close to zero) and the corresponding condition number is large, then it indicates multicollinearity (Montgomery et al., 2015).*
- *Inter-correlation among the independent variables above 0.80 signals a possible multicollinearity problem. (Montgomery et al., 2015).*

3.5.9 Regression Analysis

Regression analysis is one of the most researched and applied areas in statistics, and is used to study relationships between variables. It is a statistical methodology that is commonly applied to study the relationship of two or more variables so that the response variable Y can be described and predicted from ($p \geq 1$) predictor variables, normally denoted by $X_1, ..., X_p$. The overall analysis includes analytic methods of exploring relationships between a response variable and predictor variables. The application of regression analysis is common in business, behavioural sciences, social sciences, medical sciences, biological sciences and many other research areas (Kutner et al., 2005).

According to Beaglehole and Bonita (1993, p.67), regression analysis can be thought of as finding the best mathematical model predicting one variable with another. Linear regression analysis is a statistical technique to determine the linear relationship between two or more variables. It is primarily used for prediction and causal inferences. Regression analysis allows one to quantify the change in one variable (response) which corresponds to a given change in the explanatory variable (Pagano et al., 2000, p.415). According to Katzenellenbogen et al. (1997, p.120), regression analysis consists of a range of statistical techniques which, on the basis of mathematical models, can evaluate the inter-relationship of more than two variables. Therefore, the effect of a variable can be determined while being adjusted for the effect of other variables. To be able to investigate the more complicated sets of variables and the confounding effect of the variables, it is necessary to complete the study by using analysis known as *multiple regression*.

Definition

The general linear regression model that relates the response variable Y with p predictor variables $X_1, ..., X_p$ can be defined as

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + ...\beta_p x_{ip} + \epsilon_i, \tag{3.21}$$

where $\beta_0, ..., \beta_p$ are model parameters or partial regression coefficients. The variables $X_1, ..., X_p$ are set of known quantities assumed to be measured without error and thus designated as predictor variables, and ϵ_i is the error term that gives the random variation in Y not explained by X. The error terms ϵ_i are assumed to be random variables with mean zero and a constant variance σ^2, and to be pairwise independent.

Generally the linear multiple regression model can be presented in matrix form as

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \epsilon, \tag{3.22}$$

where

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, X = \begin{bmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1p} \\ 1 & X_{21} & X_{22} & \cdots & X_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{np} \end{bmatrix}, \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix}, \epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix},$$

where $\boldsymbol{y}$ is a n x 1 vector of observations on the response variable, $\boldsymbol{X}$ is a n x $(p+1)$ matrix of predictor variables or the design matrix with the first column of ones, and $\boldsymbol{\beta}$ is a $(p+1)$ vector of model parameters including the constant, also called partial regression coefficient. A partial regression coefficient reflects the partial effect of one predictor variable when the rest of the predicted variables included in the model are held constant. The vector $\boldsymbol{\epsilon}$ is a n x 1 vector of independent error terms with mean vector zero, and the covariance matrix, $\sigma^2\boldsymbol{I}$. The two vectors $\boldsymbol{y}$ and $\boldsymbol{\epsilon}$ are random because their elements are random variables, and $\boldsymbol{X}$ is a matrix of known constants. The classical regression analysis assumes that in a regression association only the response variable Y is assumed to be measured with error. The i^{th} row of the design matrix is the vector $\boldsymbol{x}_i' = (1, x_{i1}, ..., x_{ip})$ of observed values of p predictor variables corresponding to the response variable value measured in the i_{th} observational unit.

The regression model parameters can be performed by the method of *ordinary least squares* procedure. In this case, to estimate the parameter, we use least square equation which minimizes the error sum of squares. The least squares parameter estimates are obtained from p normal equations. The residual can be written as

$$\epsilon_i = y_i - \hat{\beta}_1 x_{i1} + ...\hat{\beta}_p x_{ip}. \tag{3.23}$$

The normal equations are:

$$\textstyle\sum_{i=1}^{n} \sum_{k=1}^{p} x_{ij} x_{ik} \hat{\beta}_k = \sum_{i=1}^{n} x_{ij} y_i, \tag{3.24}$$

where $j = 1, ..., p$.

In matrix notation, the normal equations are written as:

$$(X^T X)\hat{\beta} = X^T Y, \tag{3.25}$$

where the ij element of X is x_{ij}, the i element of the column vector Y is y_{ij}, and the j element of $\hat{\beta}$ is $\hat{\beta}_j$. Thus X is n x p, Y is n x 1, and $\hat{\beta}$ is p x 1. Therefore,

$$\hat{\beta} = (X^T X)^{-1} X^T Y, \tag{3.26}$$

3.5.9.1 The classical assumptions of linear regression model

According to Watson (1964), the basic assumptions for the linear regression analysis which need to be checked are as follows:

1. Linearity: the dependent and the independent variables should have a linear relationship.

2. Normality: the error ϵ_t at each time period t must be normally distributed, where t is the length of the series.

3. Zero mean: the error is assumed to be a random variable with a mean zero conditional on the explanatory variable.

$$E(\epsilon_t) = 0, \tag{3.27}$$

4. Homoscedasticity: the variance of the errors is constant across observations.

$$Var(\epsilon_t) = \sigma^2, \tag{3.28}$$

5. No-autocorrelation: the errors are uncorrelated.

$$Cov(\epsilon_i; \epsilon_j) = 0, \text{ for times } i \neq j$$

That is, the random error term ϵ_t, are independent and identically normally distributed with mean zero and constant variance σ^2.

$$\epsilon_t \sim N(0; \sigma^2), \text{ for times } i \neq j$$

These assumptions imply that the parameter estimates will be unbiased, consistent and efficient in the class of linear unbiased estimators (Watson, 1964).

3.5.9.2 Model diagnostics

The estimation and inference from the regression model depends on several assumptions. Therefore, one should always check validity of these assumptions and conduct analysis to examine the adequacy of the model. Gross violation of the assumptions may yield an unstable model in the sense that a different sample could lead to a totally different model with opposite conclusions. Mostly, we do not detect departures from the t or F statistics, or R^2. These are general model properties, and as such they do not ensure model adequacy.

Model assumptions need to be checked using regression diagnostics. Diagnostics methods are used to examine for instance that error variance are constant, or that there is any distributional deviation from normality. The data has to be checked for possible outliers that may exist. In general, model diagnostics methods are used to identify unusual behaviour of observations which is usually overlooked and can also be used to remedy these situations.

3.5.10 Path Modelling

Path modelling is a statistical technique used to examine causal relationships between two or more variables. The method is also known as Structural Equation Modelling (SEM). It is an extension of regression modelling in that it gives the extra flexibility of quantifying indirect and total causal effects (Bollen, 2014). That is, path modelling allows the predictor variables to influence the outcome variable directly (as in the case with regression analysis) as well as indirectly through mediating variables. The path coefficients for the full model (with all the arrows) are derived from a series of layered multiple regression analysis. For each multiple regression. the criterion is the variable in the box and the predictors are all the variables that have arrows leading to that box (Al-Ansi et al., 2015). The other characteristics of path modelling are:

- Any outcome variable in the system of equation under investigation has an error term attached to it.
- The direction of influence in the relationship of variables should be specified from the theory behind the investigation.
- The relationship between target variables is linear.
- Explanatory or predictor variables are assumed to be measured without error.

Path analysis show hypothesised causal relationship between variables and thus in essence is an extension of regression analysis (Garson, 2008). According to Wright (1921), the path coefficient is the standardised regression coefficient that predicts one variable from another. In path analysis, the association among the model should be linear in nature. The association among the models should be addictive and causal in nature. According to Wright (1920) and Wright (1923), The data that is used follow an interval type of scale. In order to reduce volatilities in the data, it is assumed in the theory of path analysis that all the error terms are not correlated among themselves.

The objective of the path analysis is to evaluate and account for the variation among all the variables at all levels, either directly or through the mediator variables. The path that leads from the exogenous variable to the endogenous variable is called the coefficient path and it is this path which constitutes the equation to be estimated. The analysis may contain several coefficient paths and that could result in a model of multiple equations for estimation.

3.6 Qualitative data

The use of qualitative research as opposed to quantitative research is motivated by the perceptions that "the ability to talk" is the only thing that can distinguish huans from the natural world. Through interviews, the researcher is engaged in abstract thinking that opens the mind to new theories emerging during the "personal experiences of the qualitative research process" (Burns and Grove, 1993; Myers et al., 1997).

Qualitative analyses are based on the definition of qualitative research. Qualitative research is defined as a type of research in which the researcher depends on the opinions of the participants. The researcher "asks broad, general questions; collects data consisting largely of words (or texts) from participants; describes and analyses these words for themes; and conducts the inquiry in a subjective, biased manner" (Creswell, 2002, p.46).

According to Lekalakala (2007, p.45), interviews are the most rewarding component of a well established communication tool that can provide rich and substantive data for the researcher. Henning et al. (2004, p.52) emphasises the importance of using this tool because of its main aim in qualitative research, which is "to bring to our attention, what individuals think, feel, do and what they have to say about it in an interview, giving us their subjective reality in a "formatted" discussion, which is guided and managed by an interviewer and later integrated into a research report". The authors further recommend the use of interviews as they are seen to be "talk-in-interaction" focusing on the analysis of conversation in everyday settings, with the aim to check "underlying structures of such talk".

Lekalakala (2007, p.45) is cited agreeing with Henning et al. (2004) about interviews that they can create "time for the respondents to reflect on the questions they were being asked, with opportunities of encouraging them to elaborate and explain in more detail the subtleties and complexities of their feelings". Vos et al. (2005, p.287) state that, "you interview because you are interested in other people's stories" because in interviews, the respondents are allowed, in a relaxed mood, to state their own views, opinions, thoughts and ideas without manipulation or interference, and without imposing the researcher's structure and assumptions.

3.7 Reliability and validity of the research

This section discusses validity and reliability issues encountered in the empirical investigation.

3.7.1 Reliability

Fraenkel and Wallen (2008, p. 147) state that, "reliability refers to the consistency of scores or answers from one administration of an instrument to another, and from one set of item to another". Kerlinger (1986, p. 405) states that the reliability of research depends on the reliability of the measuring instruments and the choice of the correct statistical procedure. Reliability is a measure based on the correlations between different items on the same test (or the same sub-scales on a large test). Reliability can be estimated through different methods.

- Test-retest method: in this method, reliability is estimated as the Pearson product-moment correlation coefficient between two administrations of the same measure. This method directly assesses the degree to which test scores are consistent from one test administration to the other (Carmines and Zeller, 1979).

- Parallel-forms method: reliability is estimated by the pearson product-moment correlation coefficient of two different forms of measurement, usually administered together. The key to this method is the development of alternate test forms that are equivalent in terms of content, response processes and statistical characteristics. This method provides partial solution to some problems inherent in the test-retest reliability method (Litwin and Fink, 1995).

- Split-half method: The split-half method assesses the internal consistency of a test, such as questionnaires and psychometric tests. A test for a single knowledge area is split into two halves and then the two halves are given to two different groups of students at the same time. This "halves reliability" estimate is then stepped up to the full test length using the Spearman-Brown prediction formula. Split-half method is an improvement of the two above mentioned methods, and it involves both the characteristics of stability and equivalence (Carmines and Zeller, 1979; Litwin and Fink, 1995).

- Internal consistency: The most common internal consistency measure is Cronbach's alpha, which is usually interpreted as the mean of all possible split-half coefficients. Cronbach's alpha is a function of the number of items in the scale and the degree of their inter-correlations. It measures the proportion of variability that is shared among items. Cronbach's alpha is a generalisation of an earlier form of estimating internal consistency, namely the Kuder-Richardson Formula 20 (Carmines and Zeller, 1979).

The general convention in this type of research has been expressed by Nunnally and Bernstein (1994) who state that one should strive for reliability values of 0.70 or higher. High levels of internal consistency were determined for the measuring instrument and its sub-scales. Rucci et al. (2007) suggested that in almost every case the Cronbach's alpha is an adequate test of reliability of data and that a minimum level of 0.7 should be adhered to for Cronbach's alpha. This minimum level was used to test reliability of the candidate's responses to the questionnaire, as quantitative data, for the study.

In addition, the statistical procedures were guided by the researcher, the supervisor and other researchers in the Department of Mathematical Statistics and Actuarial Science who are all qualified statisticians. Validated software for data analysis was used, which contributed to the reliability of the study. The reliability of the findings is strengthened by the similarity of findings from the responses on the interviews and the Likert-scale questions in the questionnaire. To assist in establishing reliability in this study, a record of the interviews have been maintained. The record is available upon request from the researcher.

3.7.2 Validity

Internal and external validity

"Validity refers to the appropriateness, meaningfulness, correctness, and usefulness of the inferences a researcher makes" (Fraenkel and Wallen, 2008, p. 147). There are two types of validity, namely, internal and external validity. The validity of the instrument is important, as discussed later in this section.

According to Kerlinger (1986, p. 300) and Welman et al. (2005, p. 107), internal validity describes the degree to which changes in the dependent variable are indeed due to the independent variable rather than to any extraneous or third variables. For this specific study, internal validity refers to the extent to which students' performance is accounted for by statistics anxiety, attitude toward statistics and mathematics self-concept and not by the confounding variables (students' age and students' class attendance). Thus, internal validity means that credible and truthful findings and interpretations are derived from the data. In the study reported here, the respondents were allowed to check the accuracy of the researcher's interpretations of their interview responses. Internal validity was also supported by the inclusion of typical quotations to justify the researcher's conclusions. This ensured that the researcher's interpretations were accurate and agreed with the experiences that the respondent tried to express by answering the questions in the interview.

External validity refers to the extent to which results of the research can confidently be generalised to the population from which the sample was selected (Kerlinger, 1986, p. 300). In this specific study the sample size was big enough to deduce that the results can be generalised to the whole target population of business calculation statistics students at the UFS during 2016, but because no random selection of the sample was done, no other generalisations can be made. As stated in Chapter 1, the applicability to a larger population can be hypothesised. Thick description was used in this study when presenting data, categories of themes, interpretations, and conclusions regarding the participants.

3.8 Ethical considerations

According to the Stevens (2013), the term ethical means "in accordance with principles of conduct that are considered correct, especially those of a given profession or group." The researcher should endeavour to ensure that research is commissioned and conducted with respect for all groups in society, regardless of race, ethnicity, religion and culture. In addition, the researcher should endeavour to balance professional integrity with respect for national and international law. Also, the researcher must ensure that the concerns of relevant stakeholders and user groups are addressed. In this section, ethical considerations that are of particular relevance to this study, namely informed consent, anonymity and confidentiality and no harm to participants, are discussed.

3.8.1 Informed consent

The research is ethical, because none of the participants suffered any physical or psychological harm through participation. Permission to conduct the study was obtained from the Head of Department of Mathematical Statistics and Actuarial Science at the University of the Free State as well as from the Dean's office of the Faculty of Natural and Agricultural Sciences. Students in the target population were briefed about the aim and purpose of the questionnaire and the researcher answered all questions that the students had about the research. The researcher respected the right of any individual to refuse to participate in the study or to withdraw from participating at anytime. Students were assured that participation in the research was voluntary and that all data obtained would remain confidential. Regarding the interviews, verbal informed consent were obtained from the students to record the results. All participants were offered the option not to answer questions which they feel uncomfortable with.

3.8.2 Anonymity and confidentiality

The researcher assured the participants that all information would remain confidential and anonymous. Questionnaires were labeled with a code number which was known to the student and researcher only. Subjects are identified only by their code number in the study to ensure that the data cannot be linked to individual participants. All collected data are kept confidential and were used only for research purpose. Individual students cannot be identified from any data or data summaries presented in this study. Furthermore, all audio cassettes will be destroyed as soon as the study has been completed.

3.8.3 Protection from harm

The researcher ensured that participants were not exposed to any undue physical or psychological harm, e.g. discomfort, harassment, or invasion of privacy. In addition, care was taken to ensure that students were not influenced negatively by not participating in the study. The researcher also strived to be honest, respectful and sympathetic towards all participants.

3.9 Conclusion

This chapter focused on the research design and methodology of the study. The chapter began with a statement of the research problem, the study's hypotheses and an overview of methods used. Detailed information on the dependent and independent variables were presented and the design and methodology of the research were discussed with reference to the data collection and measuring instruments. In the remainder of the chapter the investigation was discussed in terms of the following: overview of the research methods, population and sampling, questionnaires, data collection techniques, measuring instruments, and data analysis procedures.

Lastly, an overview of validity, reliability, and ethical considerations was given. The results of the study will be presented, interpreted and discussed in the next chapter.

Chapter 4

Results, Data analysis and Discussion of findings

4.1 Introduction

The previous chapter provided background on the research design, methodology and data collection methods. In addition, it provided background on the approach used to analyse the STARS questionnaire and the approach used to gather qualitative information on the experiences of students regarding statistics anxiety, attitude toward statistics and mathematics self-concept.

The following chapter presents the statistical methods used to analyse the data, together with discussions on the findings from the data analysis process and deals with results of the empirical study.

4.2 Descriptive Analysis

Descriptive statistics are used to describe the collected data by investigating the distribution of scores obtained for all the variables, and then to determine whether there is any relationship between the variable scores. The aim is to obtain a picture of the data collected during the research.

4.2.1 Gender and STARS Questionnaire

Table 4.1 presents information on the distribution of the gender of the participants. The sample consisted of 103 participants of whom 51.5% were females and 48.5% were males.

Table 4.1: Gender of participants.

Gender	Frequency	Percent
Female	53	51.5
Male	50	48.5
Total	103	100

Table 4.2 presents the mean scores and standard deviations for each section of STARS across the three administrations. There is an increase level of students' Anxiety toward Statistics and Attitude toward Statistics from the first administration to second administration. Anxiety toward Statistics decreased from March to June but however, attitude toward statistics increased from March to June. Mathematics Self-concept decreased from February to March and then increased from the March to June.

Table 4.2: Mean (standard deviation) for the three STARS sections across the three administrations.

	Administration Time		
Sections	February	March	June
Anxiety toward Statistics	3.15 (0.66)	3.48 (0.75)	3.07 (0.80)
Attitude toward Statistics	2.36 (0.62)	2.58 (0.63)	2.61 (0.81)
Mathematics Self-concept	2.35 (0.41)	2.30 (0.39)	2.39 (0.42)

Figure 4.1 presents the graphical representation for students' average scores in three sections of STARS discussed in Table 4.2.

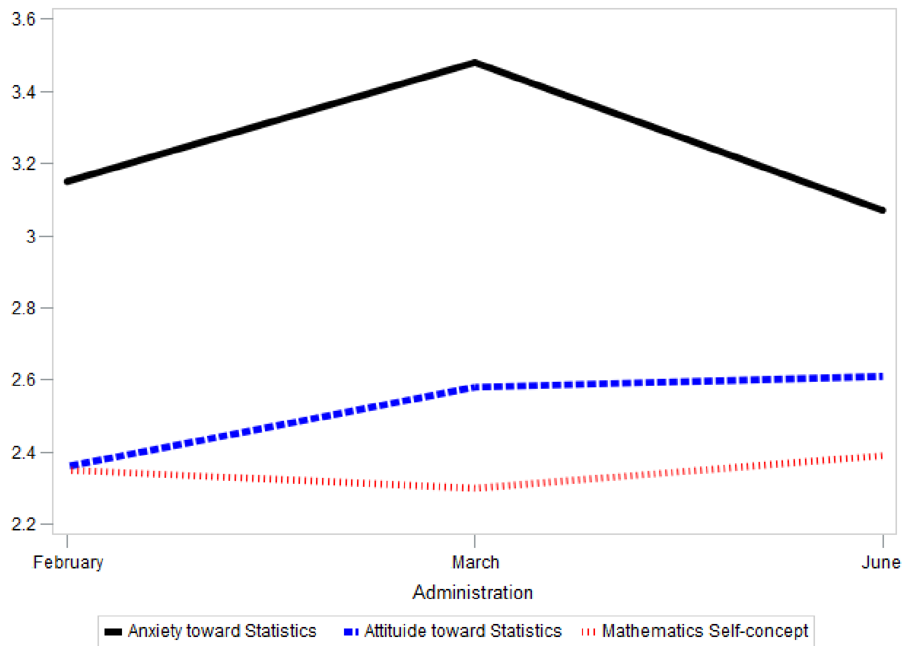


Figure 4.1: Students' average scores for the three sections of STARS across the three administrations.

Table 4.3 presents the means and standard deviations for the six anxiety sub-scales of STARS. Five of anxiety sub-scales increased from February to March, however, Interpretation Anxiety decreased from February to March and from March to June. This results indicates that students level of anxiety increased from February to March except for Interpretation Anxiety. The results further indicates that four of the anxiety sub-scales decreased from March to June, meaning for all those four sub-scales, students' level of anxiety decreased from March to June. However, for the other two sub-scales, Worth of Statistics and Computation Self-concept, they both increased from March to June. These results may suggest that students recognised the value of taking a statistics course and became more confident in doing mathematical calculations toward the end of the course.

Table 4.3: Mean (standard deviation) for the STARS six anxiety sub-scales.

	Administration Time		
Sub-scales	February	March	June
Test and Class Anxiety	3.22 (0.74)	3.31 (0.78)	3.20 (0.90)
Interpretation Anxiety	3.10 (0.74)	2.94 (0.77)	2.85 (0.78)
Fear of Asking for Help	3.15 (0.835)	3.30 (0.890)	3.22 (0.973)
Worth of Statistics	2.38 (0.66)	2.59 (0.67)	2.64 (0.82)
Fear of the Teacher	2.36 (0.69)	2.51 (0.74)	2.44 (0.89)
Computation Self-concept	2.28 (0.80)	2.60 (0.81)	2.66 (0.92)

Graphical representation of students' average anxiety scores for each sub-scale across the three administrations are given in Figure 4.2.

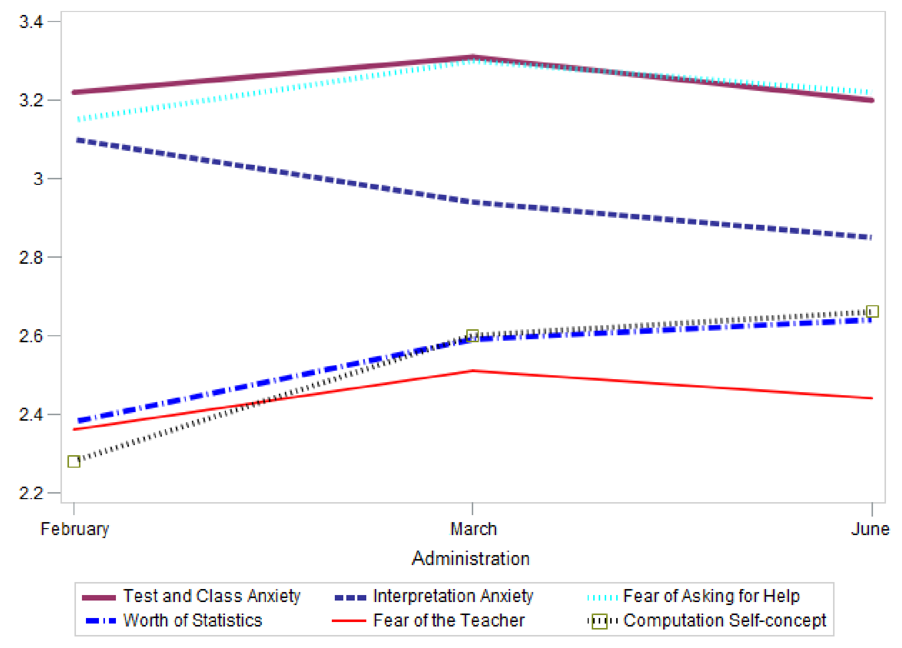


Figure 4.2: Students' average anxiety scores for the STARS six sub-scales across the three administrations.

4.2.2 Cronbach's alpha test for reliability

Internal consistency, or reliability, is measured by analysing statements in a questionnaire that assessed the similar theme. There are several measures of reliability found in the literature, as observed by Nunnally and Bernstein (1994) and Tavakol and Dennick (2011). These reliability estimates are factor analysis, generalisability theory, item-response theory, half-split techniques and Cronbach's alpha index. In this study, reliability was estimated by performing an internal consistency test using Cronbach's alpha coefficient (α).

The Cronbach's alpha coefficients of these adapted instruments were observed in order to determine the reliability and thus how free the scales were from random error. The Cronbach's alpha for all the overall constructs under investigation in the present study were 0.72 and 0.738, confirming their reliability or good internal consistency, since Nunnally and Bernstein (1994) stated that the Cronbach's alpha coefficient of scale should ideally be greater than 0.7 to be considered reliable.

All sub-scales in Table 4.4 and 4.5 do produce Cronbach's alpha (α) that indicate internal consistency. Therefore, measurement for the statements in the STARS questionnaire can be considered valid for this study.

Table 4.4: Cronbach's alpha for the three sections of STARS.

Scale (Domain)	Number of items	Cronbach's alpha (February)	Cronbach's alpha (March)	Cronbach's alpha (June)
Anxiety toward Statistics	11	0.73	0.715	0.77
Attitude toward Statistics	25	0.71	0.76	0.74
Mathematics Self-concept	10	0.713	0.681	0.706
Overall reliability				**0.72**

Table 4.5: Cronbach's alpha for the six anxiety sub-scales.

Scale (Domain)	Number of items	Cronbach's alpha (February)	Cronbach's alpha (March)	Cronbach's alpha (June)
Test and Class Anxiety	7	0.76	0.73	0.71
Interpretation Anxiety	5	0.724	0.75	0.73
Fear of Asking for Help	7	0.77	0.81	0.756
Worth of Statistics	4	0.801	0.79	0.778
Fear of the Teacher	5	0.694	0.705	0.73
Computation Self-concept	8	0.786	0.83	0.75
Overall reliability				**0.738**

4.2.3 Tests and Examination Marks.

Figure 4.3 presents the students' average performance for the two tests and examination. Test 2 scores were lower than that of Test 1, while the Examination scores were high than Test 2 scores.

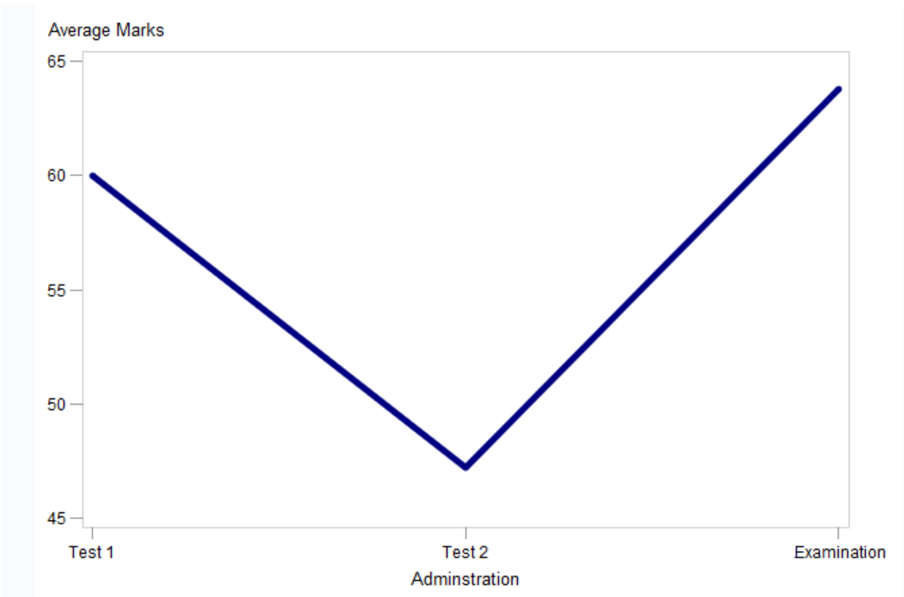


Figure 4.3: Students' average tests and examination scores.

This result is echoed across the gender split (Figure 4.4). Both males and females reported decrease in performance from Test 1 to Test 2, then an increase from Test 2 to the Examination.

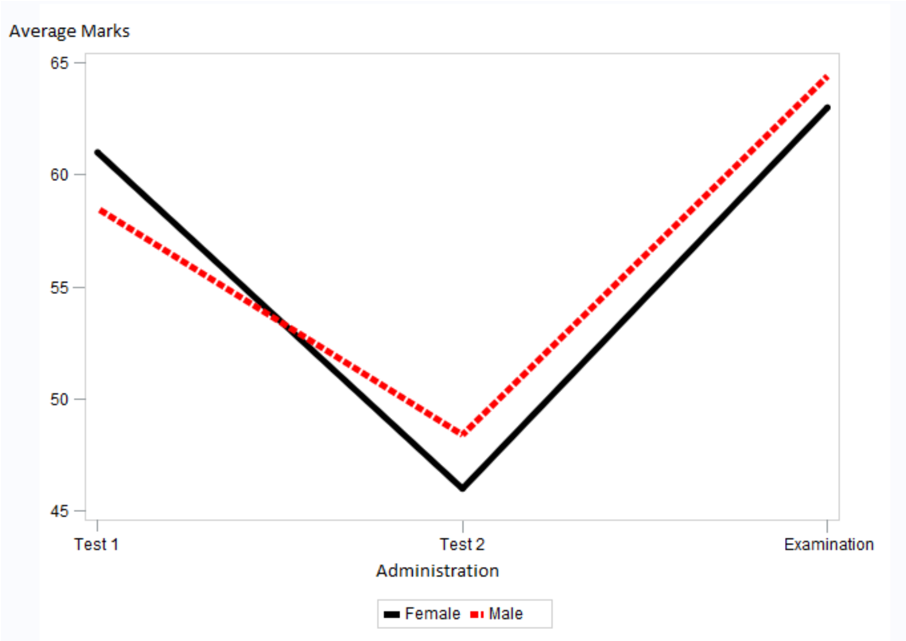


Figure 4.4: Comparison between gender average tests and examination scores.

4.3 Test of Normality

In statistics it is conventional to assume that the data are normally distributed. Many analysis frameworks are grounded on this assumption and if this assumption is violated the inference may not be reliable or valid. For this reason it is essential to check or test normality assumption before any statistical analysis of data is performed. A variety of tests of normality have been developed by various researchers. In this study two ways will be considered to test normality, namely the statistical approach (Kolmogorov- Smirnov test, Shapiro-Wilks test, Skewness, Kurtosis) and the graphical approach (quantile-quantile plot).

Tests for normality calculate the probability that the sample was drawn from a normal population. The hypotheses used are:

H_0: Sample data follow a normal distribution.

H_1: Sample data do not follow a normal distribution.

4.3.1 Statistical approach

Statistical tests for normality are more precise than graphical or ad-hoc methods since actual probabilities are calculated. The statistical methods covered in this section are the Kolmogorov- Smirnov test, the Shapiro-Wilks test and skewness and kurtosis tests. Both the Kolmogorov- Smirnov test and the Shapiro-Wilks test are non-parametric tests that allow one to check the shape of a sample against a variety of known, popular shapes, including the normal distribution. If the resulting p-value is under 0.05, then we have significant evidence that the sample is no normally distributed. Besides these two tests, a common "rule of thumb" test for normality is to run descriptive statistics to get skewness and kurtosis, then divide these values by sample standard error. The ratio of skewness to its standard error is used as a test of normality, and should be within the range of ± 1.96. In addition, the ratio of kurtosis to its standard error is also used as a test for normality, and should be within the range of ± 3. Normal distribution produces a kurtosis statistic of approximately or close to zero. Therefore, a kurtosis statistic close to zero would be an acceptable kurtosis value for a mesokurtic distribution (having the same kurtosis as the normal distribution).

Table 4.6 presents statistical tests of normality. The normality tests (Kolmogorov-Smirnov and Shapiro-Wilks) are statistically not significant in all three sections of STARS. For both tests the p-value is greater than 0.05 so we can accept the null hypothesis that the data come from a normally-distributed population. In addition, the values for asymmetry and kurtosis range between ± 1.96 and ± 3 respectively, supporting the normality assumptions within the three sections of STARS.

Table 4.6: Normality test for the three average sections of STARS.

	Kolmogorov- Smirnov		Shapiro-Wilks			
	Statistic	p-value	Statistic	p-value	Skewness	Kurtosis
Anxiety toward Statistics	0.073	0.200	0.981	0.137	-1.815	0.367
Attitude toward Statistics	0.078	0.130	0.978	0.090	0.857	0.977
Mathematics Self-concept	0.072	0.200	0.986	0.355	1.559	0.911

* Significant at the 5% level

Table 4.7 presents statistical tests of normality for the six anxiety sub-scales. The normality tests (Kolmogorov- Smirnov and Shapiro-Wilks) are statistically not significant. The two tests' p-values are greater than 0.05 and therefore we fail to reject null hypotheses that the data are normally distributed. In addition, the values for skewness and kurtosis range between ± 1.96 and ± 3 respectively in all six sub-scales, within the range of normality.

Table 4.7: Normality test for the six average anxiety sub-scales.

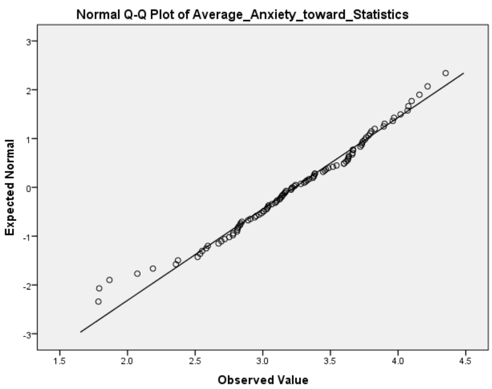
	Kolmogorov- Smirnov		Shapiro-Wilks			
	Statistic	p-value	Statistic	p-value	Skewness	Kurtosis
Test and Class Anxiety	0.061	0.200	0.984	0.231	-1.269	0.235
Interpretation Anxiety	0.088	0.050	0.985	0.279	-1.328	0.528
Fear of Asking for Help	0.079	0.110	0.987	0.399	-0.992	0.347
Worth of Statistics	0.076	0.155	0.978	0.084	1.126	1.430
Fear of the Teacher	0.065	0.200	0.994	0.935	-0.269	-0.244
Computation Self-concept	0.055	0.200	0.987	0.440	0.597	-0.805

* Significant at the 5% level

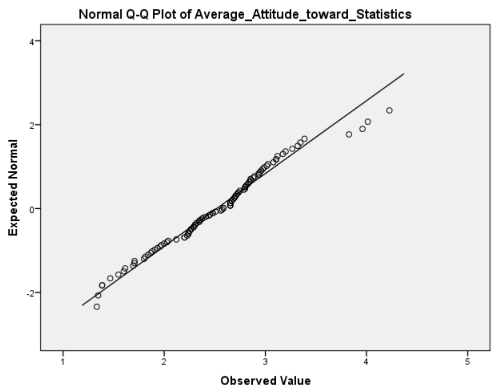
4.3.2 Graphical approach

Graphical methods visualise the distribution of a random variable and compare the distribution to a theoretical one using plots. In this study, quantile-quantile plots (Q-Q plot) will be drawn as part of the graphical approach. A Q-Q plot compares ordered values of a variable with quantiles of a specific theoretical distribution (in this case the normal distribution). If the two distributions match, the points on the plot will form a linear pattern passing through the origin with a unit slope. This plot is used to see how well a theoretical distribution models the empirical data. Graphical approaches provide powerful diagnostic tools for confirming assumptions, or, when the assumptions are not met, for suggesting corrective actions. A fairly linear, 45° pattern in a normal quantile plot suggests that it is reasonable to assume that the data come from a normal distribution.

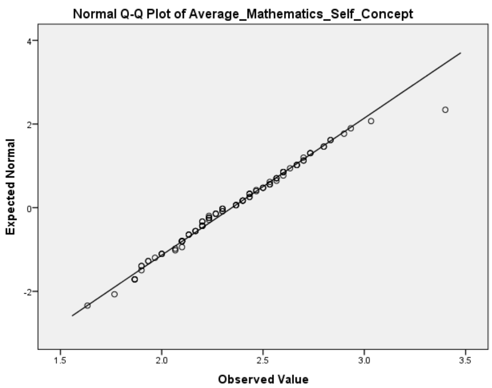
Figure 4.5 presents the graphical approach for the three sections of STARS. The statistical methods results in Table 4.6 are confirmed by visual inspection of the Q-Q plot of the same data shown in Figure 4.5. The normal Q-Q plots for the three sections of STARS look reasonably normal (i.e data points are close to the diagonal lines with exception of some few extreme points) and hence we judge this data ready for analysis using methods based on the assumption of normality.



(a) Average Anxiety toward Statistics



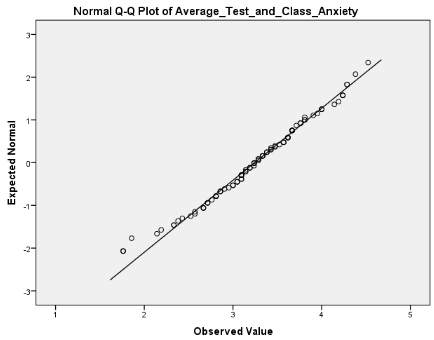
(b) Average Attitude toward Statistics



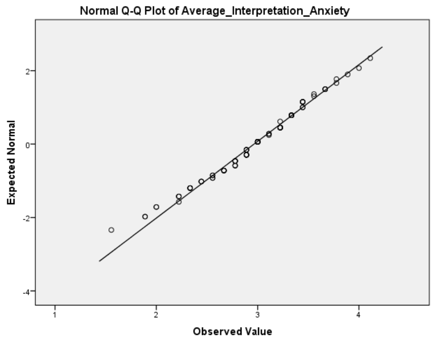
(c) Average Mathematics Self-concept

Figure 4.5: Normal Quantile-Quantile plots for the three sections of STARS.

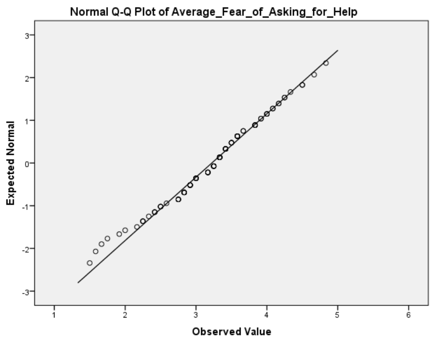
Figure 4.6 presents the graphical approach for the six anxiety sub-scales. The statistical methods results in Table 4.7 are confirmed by visual inspection of the Q-Q plot of the same data shown in Figure 4.6. The normal Q-Q plots for the six anxiety sub-scales look reasonably normal (i.e data points are close to the 45° diagonal lines with exception of a few extreme points) and hence we judge this data ready for analysis using methods based on the assumption of normality.



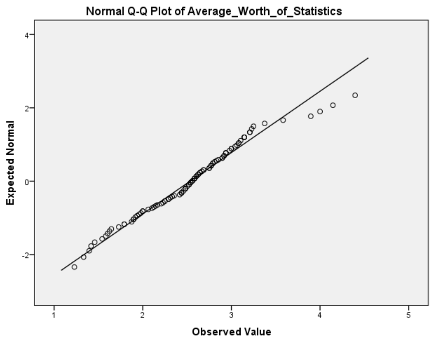
(a) Average Test and Class Anxiety



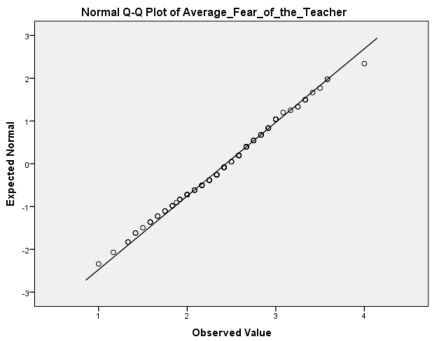
(b) Average Interpretation Anxiety



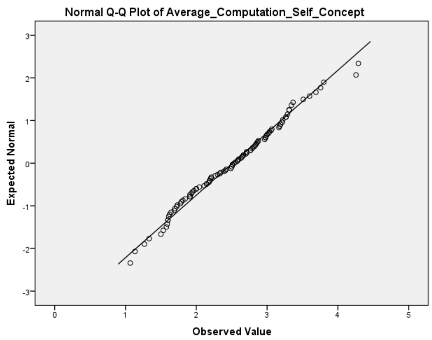
(c) Average Fear of Asking for Help



(d) Average Worth of Statistics



(e) Average Fear of the Teacher



(f) Average Computation Self-concept

Figure 4.6: Normal Quantile-Quantile plots for the six anxiety sub-scales.

4.4 Paired samples t-test

The paired samples t-test compares two means that are from the same individuals or related units. The purpose of the test is to determine whether there is statistical evidence that the mean difference between paired observations on a particular outcome is significantly different from zero. Table 4.8 presents paired samples t-test results for the three sections of STARS. Preliminary assumption testing was conducted to check that the data are continuous, normality and that the sample of pairs is simple random sample. Anxiety toward Statistics between any pair of times differed significantly except the time period February and June. This suggests that Anxiety toward Statistics changed significantly across the semester except the February and June. The difference in Attitude toward Statistics from February to March and from February to June was significant. This suggests that students developed different levels of attitude regarding the subject matter of statistics during the semester. However, there was no significant difference in Attitude toward Statistics from March to June (t=-0.160, p=0.873). Mathematics Self-concept changed significantly from March to June, meaning that students gained more confidence in doing mathematics during this period. However, there was no significant difference from February to March and from February to June.

Table 4.8: Comparisons between the three administrations of the STARS questionnaire for the three sections of STARS.

	February- March		March- June		February- June	
	t-value (df=102)	p-value	t-value (df=102)	p-value	t-value (df=102)	p-value
Anxiety toward Statistics	-3.873	0.000*	5.069	0.000*	0.842	0.402
Attitude toward Statistics	-3.870	0.000*	-0.623	0.535	-3.147	0.001*
Mathematics Self-concept	1.285	0.202	-2.014	0.047*	-0.859	0.392

* Significant at the 5% level

Table 4.9 presents the paired samples t-test results for the six anxiety sub-scales of STARS across the three administrations. There was no statistically significant difference between any pair of times for sub-scales Test and Class Anxiety, Fear of Asking for Help and Fear of the Teacher. This indicates that students' levels of anxiety in those three sub-scales did not differ or change over time across the semester.

Interpretation Anxiety did not differ significantly except for the pair of times February and June, meaning that Interpretation Anxiety differed significantly at pair of time February to June. There was a significant difference for the subs-scales Worth of Statistics and Computation Self-concept from February to March and from February to June, but no significant difference from March to June. Indicating that students recognised the value of taking a statistics module and that students had anxiety toward computation or mathematical principles in statistics module.

Table 4.9: Comparison for the STARS sub-scales for the three administrations.

	February- March		March- June		February- June	
	t-value (df=102)	p-value	t-value (df=102)	p-value	t-value (df=102)	p-value
Test and Class Anxiety	-0.970	0.334	1.256	0.212	0.225	0.823
Interpretation Anxiety	1.756	0.082	0.874	0.384	2.359	0.020*
Fear of Asking for Help	-1.431	0.156	0.848	0.398	-0.539	0.591
Worth of Statistics	-3.291	0.001*	-0.746	0.457	-3.484	0.001*
Fear of the Teacher	-1.887	0.062	0.646	0.520	-0.908	0.366
Computation Self-concept	-4.209	0.000*	-0.728	0.468	-3.896	0.000*

* Significant at the 5% level

4.5 Gender Differences: MANOVA

Multivariate analysis of variance was performed to investigate gender differences. MANOVA is a dependence technique that measures the difference between groups of two or more metric dependent variables simultaneously. Preliminary assumption testing was conducted to check multivariate normality, linearity, univariate and multivariate outliers and homogeneity of variance covariance matrices, with no serious violations noted. One of the assumptions for MANOVA is that the variance-covariance matrices are equal for all treatment groups. The Box's M statistic tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups, and has been reported before each MANOVA test.

When researchers work with multiple independent variables in a study and decide to analyse one independent variable at a time, they will inadvertently increase Type I error rates. Furthermore, single-factor independent variable assessments do not allow researchers to determine how independent variables jointly affect the dependent variables. Multivariate statistical analysis is concerned with data collected on several dimensions of the same individual. In one-way MANOVA, the interest is in comparing the treatment effects, which correspond to a single variable. When there are two factors such as factor "A" and factor "B" with different levels, various models can be obtained by combining the two factors.

If factor "A" has different a-levels and factor "B" with b-levels; the experiment will consist of "a x b" treatment combination. In this case, the two factors will cross with each other, and the design will often be referred to as a two-way classification (Stevens, 2012). The two-way situation is sometimes referred to as a factorial or two-way MANOVA, where the effects of two factors are examined simultaneously on the dependent variables. The assumptions of independence, normality and homogeneity of variance-covariance matrices are comparable to one-way MANOVA.

4.5.1 Two-way MANOVA for the three sections of STARS: Gender and Time

Table 4.11 presents two-way MANOVA results for the three sections of STARS. The focus of the present section will be to analyse two-way MANOVA, where the researcher has two independent variables (gender and time) and three dependent variables namely: Anxiety toward Statistics, Attitude toward Statistics and Mathematics Self-concept. Four multivariate tests to evaluate any main effects are commonly employed in computerised statistical programs: Pillai's trace, Wilks' lambda, Hotelling's trace, and Roy's largest root. The most prominent of these tests in the research literature is Wilks' lambda. Because Wilks' lambda is an inverse criterion, smaller values provide more evidence of treatment effects (Stevens, 2012).

Table 4.10 presents a significant Box's M test (p-value=0.012), which indicates violation of homogeneity of covariance matrices assumption. The null hypothesis for this test is that the observed covariance matrices for the dependent variables are equal across the groups. Thus we highlight Pillai's Trace test (a statistic that is very robust and not highly linked to assumptions about the normality of the distribution of the data) for the MANOVA results.

Table 4.10: Box's test for Equality

Box's M	51.531
F	1.674
df 1	30
df 2	206224.589
p-value	0.012

Table 4.11 presents the two-way MANOVA results for the three sections of STARS. There is a time main effect, a slightly significant gender effect, and no significant interaction over and above main effects, F=[0.344], p-value=[0.914]; Pillai's Trace= [0.007].

Table 4.11: Two-way MANOVA for the three sections of STARS.

Effect		Value	F	H_0 df	Error df	P-value
Gender	Pillai's Trace	0.023	2.384	3	301	0.069
	Wilks' Lambda	0.977	2.384	3	301	0.069
	Hotelling-Lawley Trace	0.024	2.384	3	301	0.069
	Roy's Largest Root	0.024	2.384	3	301	0.069
Time	Pillai's Trace	0.093	4.899	6	604	0.000*
	Wilks' Lambda	0.909	4.903	6	602	0.000*
	Hotelling-Lawley Trace	0.098	4.907	6	600	0.000*
	Roy's Largest Root	0.070	7.022	3	302	0.000*
Gender * Time	Pillai's Trace	0.007	0.344	6	604	0.914
	Wilks' Lambda	0.993	0.343	6	602	0.914
	Hotelling-Lawley Trace	0.007	0.341	6	600	0.915
	Roy's Largest Root	0.004	0.452	3	302	0.716

* Significant at the 5% level

The slight significance of gender is due to slight gender differences apparent in the February data.

4.5.2 Gender difference for the three sections of STARS: February.

Table 4.12 presents descriptive statistics for the three sections of STARS for the month of February. An inspection of the mean scores indicated that females reported higher levels of anxiety than males. However, the differences were not significant.

Table 4.12: Descriptive statistics for gender difference for February administration.

	Mean	SD	MD	F	p-value
Anxiety toward Statistics			0.18	2.088	0.152
Male	3.053	0.7109			
Female	3.238	0.5908			
Attitude toward Statistics			0.26	2.646	0.163
Male	2.222	0.5412			
Female	2.482	0.6744			
Mathematics Self-concept			0.063	0.618	0.434
Male	2.318	0.389			
Female	2.381	0.424			

* Significant at the 5% level
Note: SD= Standard deviation, MD= Mean difference (Female - Male)

Table 4.13 presents the Box's test of equality of covariance matrices to check the assumption of homogeneity of covariance across the groups. The null hypothesis for this test is that the observed covariance matrices for the dependent variables are equal across the groups. The Box's M test (7.689) was not significant, p-value (0.282) $> \alpha$ (0.05). Indicating that there are no significant differences between the covariance matrices. Therefore, the assumption is not violated and Wilk's Lambda is an appropriate test to use.

Table 4.13: Box's test for Equality

Box's M	7.689
F	1.240
df 1	6
df 2	73215.84
p-value	0.282

The results of multivariate analysis of variance are shown in Table 4.14. Three dependent variables for the month of February were used: Anxiety toward Statistics, Attitude toward Statistics and Mathematics Self-concept. The independent variable was gender. There is partial statistical significance (p-value < 0.1) for gender for the month of February on the combined dependent variables, F = [2.303]; p-value = [0.082]; Wilk's Lambda = [0.935]; partial eta squared = [0.065].

Table 4.14: Multivariate tests for the three sections administered in February

Effect		Value	F	H_0 df	Error df	P-value
Gender	Pillai's Trace	0.065	2.30	3	99	0.082
	Wilk's Lambda	0.935	2.30	3	99	0.082
	Hotelling-Lawley Trace	0.070	2.30	3	99	0.082
	Roy's Largest Root	0.070	2.30	3	99	0.082

* Significant at the 5% level

4.5.3 Gender difference for the three sections of STARS: March.

Table 4.15 presents descriptive statistics for the three sections of STARS for the month of March. An inspection of the mean scores indicated that females reported higher levels of anxiety than males. However, the differences were not significant.

Table 4.15: Descriptive statistics for gender difference for March administration.

	Mean	SD	MD	F	p-value
Anxiety toward Statistics			0.201	1.865	0.175
Male	3.376	0.794			
Female	3.577	0.702			
Attitude toward Statistics			0.114	0.842	0.361
Male	2.526	0.649			
Female	2.640	0.620			
Mathematics Self-concept			-0.019	0.061	0.806
Male	2.306	0.414			
Female	2.287	0.375			

* Significant at the 5% level
Note: SD= Standard deviation, MD= Mean difference (Female - Male)

Table 4.16 presents the Box's test of equality of covariance matrices to check the assumption of homogeneity of covariance across the groups for the second administration. The null hypothesis for this test is that the observed covariance matrices for the dependent variables are equal across the groups. The Box's M test (7.299) was not significant, p-value (0.315) > α (0.05). Indicating no significant differences between the covariance matrices. Therefore, the assumption is not violated and Wilk's Lambda is an appropriate test to use.

Table 4.16: Box's test for Equality

Box's M	7.299
F	1.177
df 1	6
df 2	73215.84
p-value	0.315

Table 4.17 presents the results for multivariate analysis of variance. Three dependent variables for the month of March were used: Anxiety toward Statistics, Attitude toward Statistics and Mathematics Self-concept. The independent variable was gender. There was no statistically significant difference between males and females for the month of March on the combined dependent variables, F = [0.635]; p-value = [0.594]; Wilk's Lambda = [0.981]; partial eta squared = [0.019].

Table 4.17: Multivariate tests for the three sections administered in March

Effect		Value	F	H_0 df	Error df	P-value
Gender	Pillai's Trace	0.019	0.635	3	99	0.594
	Wilk's Lambda	0.981	0.635	3	99	0.594
	Hotelling-Lawley Trace	0.019	0.635	3	99	0.594
	Roy's Largest Root	0.019	0.635	3	99	0.594

* Significant at the 5% level

4.5.4 Gender difference for the three sections of STARS: June.

Table 4.18 presents descriptive statistics for the three sections of STARS for the month of June. An inspection of the mean scores indicated that females reported higher levels of anxiety than males. However, the differences were not significant.

Table 4.18: Descriptive statistics for gender difference for June administration.

	Mean	SD	MD	F	p-value
Anxiety toward Statistics			0.183	1.371	0.244
Male	2.975	0.72			
Female	3.158	0.858			
Attitude toward Statistics			0.065	0.166	0.684
Male	2.578	0.758			
Female	2.643	0.864			
Mathematics Self-concept			0.07	0.705	0.403
Male	2.356	0.469			
Female	2.426	0.392			

* Significant at the 5% level
Note: SD= Standard deviation, MD= Mean difference (Female - Male)

Table 4.19 presents the Box's test of equality of covariance matrices to check the assumption of homogeneity of covariance across the groups. The Box's M test (6.147) was not significant, p-value (0.429) $>$ α (0.05). Indicating that there are no significant differences between the covariance matrices. Therefore, the assumption is not violated and Wilk's Lambda is an appropriate test to use.

Table 4.19: Box's test for Equality

Box's M	6.147
F	0.991
df 1	6
df 2	73215.84
p-value	0.429

Table 4.20 presents the results for multivariate analysis of variance. Three dependent variables for the month of June were used: Anxiety toward Statistics, Attitude toward Statistics and Mathematics Self-concept. The independent variable was gender. There was no statistically significant difference between males and females for the month of June on the combined dependent variables, F = [0.764]; p-value = [0.517]; Wilk's Lambda = [0.977]; partial eta squared = [0.023].

Table 4.20: Multivariate tests for the three sections administered in June

Effect		Value	F	H_0 df	Error df	P-value
Gender	Pillai's Trace	0.023	0.764	3	99	0.517
	Wilk's Lambda	0.977	0.764	3	99	0.517
	Hotelling-Lawley Trace	0.023	0.764	3	99	0.517
	Roy's Largest Root	0.023	0.764	3	99	0.517

* Significant at the 5% level

4.5.5 Two-way MANOVA for six anxiety sub-scales: Gender and Time

Table 4.22 presents two-way MANOVA results for the six anxiety sub-scales. The focus of the present section will be to analyse two-way MANOVA, where the researcher has two independent variables (gender and time) and six dependent variables, namely: Test and Class Anxiety, Interpretation Anxiety, Fear of Asking for Help, Worth of Statistics, Fear of the Teacher and Computation Self-concept. Table 4.21 presents a significant Box's M test (p-value=0.029), which indicates violation of homogeneity of covariance matrices assumption. The null hypothesis for this test is that the observed covariance matrices for the dependent variables are equal across the groups. Thus we highlight Pillai's Trace test (a statistic that is very robust and not highly linked to assumptions about the normality of the distribution of the data) for the MANOVA results.

Table 4.21: Box's test for Equality

Box's M	141.226
F	1.278
df 1	105
df 2	146615.056
p-value	0.029

Table 4.22 presents the two-way MANOVA results for the six anxiety sub-scales. There is a time main effect, a slightly significant gender effect, and no significant interaction over and above main effects, F=[1.168], p-value=[0.302]; Pillai's Trace= [0.046].

Table 4.22: Two-way MANOVA for six anxiety sub-scales.

Effect		Value	F	H_0 df	Error df	P-value
Gender	Pillai's Trace	0.044	2.306	6	298	0.034*
	Wilks' Lambda	0.956	2.306	6	298	0.034*
	Hotelling-Lawley Trace	0.046	2.306	6	298	0.034*
	Roy's Largest Root	0.046	2.306	6	298	0.034*
Time	Pillai's Trace	0.087	2.270	12	598	0.008*
	Wilks' Lambda	0.913	2.299	12	594	0.007*
	Hotelling-Lawley Trace	0.094	2.320	12	594	0.006*
	Roy's Largest Root	0.087	4.320	6	299	0.000*
Gender * Time	Pillai's Trace	0.046	1.168	12	598	0.302
	Wilks' Lambda	0.954	1.173	12	596	0.299
	Hotelling-Lawley Trace	0.048	1.178	12	594	0.295
	Roy's Largest Root	0.043	2.135	6	299	0.049*

* Significant at the 5% level

4.5.6 Gender difference for six anxiety sub-scales: February.

Table 4.23 presents descriptive statistics for the six anxiety sub-scales for the month of February. An inspection of the mean scores indicated that females reported higher levels of anxiety than males. However, only three sub-scales were statistically significant: Test and Class Anxiety, Fear of Asking for Help and Worth of Statistics.

Table 4.23: Descriptive statistics for gender difference for February administration.

	Mean	SD	MD	F	p-value
Test and Class Anxiety			0.312	4.698	0.033*
Male	3.063	0.768			
Female	3.375	0.692			
Interpretation Anxiety			-0.123	0.714	0.400
Male	3.167	0.786			
Female	3.044	0.686			
Fear of Asking for Help			0.331	4.168	0.044*
Male	2.985	0.893			
Female	3.316	0.750			
Worth of Statistics			0.325	6.697	0.011*
Male	2.210	0.570			
Female	2.535	0.695			
Fear of the Teacher			0.062	0.204	0.652
Male	2.330	0.628			
Female	2.392	0.744			
Computation Self-concept			0.213	1.855	0.176
Male	2.172	0.706			
Female	2.385	0.867			

* Significant at the 5% level
Note: SD= Standard deviation, MD= Mean difference (Female - Male)

Table 4.24 presents the Box's test of equality of covariance matrices to check the assumption of homogeneity of covariance across the groups. The null hypothesis for this test is that the observed covariance matrices for the dependent variables are equal across the groups. The Box's M test (24.830) was not significant, p-value (0.331) $> \alpha$ (0.05). Indicating that there are no significant differences between the covariance matrices. Therefore, the assumption is not violated and Wilk's Lambda is an appropriate test to use.

Table 4.24: Box's test for Equality

Box's M	24.830
F	1.107
df 1	21
df 2	37244.40
p-value	0.331

Table 4.25 presents the results for multivariate analysis of variance. Six anxiety sub-scales were dependent variables for the month of February. The independent variable was gender. There was statistically significant difference between males and females for the month of February on the combined dependent variables, F = [2.635]; p-value = [0.021]; Wilk's Lambda = [0.859]; partial eta squared = [0.141].

Table 4.25: Multivariate tests for the six anxiety sub-scales in February.

Effect		Value	F	H_0 df	Error df	P-value
Gender	Pillai's Trace	0.141	2.635	6	96	0.021
	Wilk's Lambda	0.859	2.635	6	96	0.021
	Hotelling-Lawley Trace	0.165	2.635	6	96	0.021
	Roy's Largest Root	0.165	2.635	6	96	0.021

* Significant at the 5% level

4.5.7 Gender difference for the six anxiety sub-scales: March.

Table 4.26 presents descriptive statistics for the six anxiety sub-scales for the month of March. An inspection of the mean scores indicated that females reported higher levels of anxiety than males. However, the differences were not significant.

Table 4.26: Descriptive statistics for gender difference for March administration.

	Mean	SD	MD	F	p-value
Test and Class Anxiety			0.218	2.042	0.156
Male	3.197	0.851			
Female	3.415	0.693			
Interpretation Anxiety			0.166	1.207	0.275
Male	2.853	0.720			
Female	3.019	0.804			
Fear of Asking for Help			0.216	1.524	0.220
Male	3.185	0.970			
Female	3.401	0.802			
Worth of Statistics			0.157	1.438	0.233
Male	2.508	0.692			
Female	2.665	0.642			
Fear of the Teacher			-0.017	0.013	0.908
Male	2.515	0.790			
Female	2.498	0.697			
Computation Self-concept			0.012	0.005	0.941
Male	2.592	0.819			
Female	2.604	0.799			

* Significant at the 5% level
Note: SD= Standard deviation, MD= Mean difference (Female - Male)

Table 4.27 presents the Box's test of equality of covariance matrices to check the assumption of homogeneity of covariance across the groups. The Box's M test (29.207) was not significant, p-value (0.160) > α (0.05). Indicating that there are no significant differences between the covariance matrices. Therefore, the assumption is not violated and Wilk's Lambda is an appropriate test to use.

Table 4.27: Box's test for Equality

Box's M	29.207
F	1.302
df 1	21
df 2	37244.40
p-value	0.160

Table 4.28 presents the results for multivariate analysis of variance. Six anxiety sub-scales were dependent variables for the month of March. The independent variable was gender. There was no statistically significant difference between males and females for the month of March on the combined dependent variables, F = [1.119]; p-value = [0.357]; Wilk's Lambda = [0.935]; partial eta squared = [0.065].

Table 4.28: Multivariate tests for the six anxiety sub-scales in March.

Effect		Value	F	H_0 df	Error df	P-value
Gender	Pillai's Trace	0.065	1.119	6	96	0.357
	Wilk's Lambda	0.935	1.119	6	96	0.357
	Hotelling-Lawley Trace	0.70	1.119	6	96	0.357
	Roy's Largest Root	0.70	1.119	6	96	0.357

* Significant at the 5% level

4.5.8 Gender difference for the six anxiety sub-scales: June.

Table 4.29 presents descriptive statistics for the six anxiety sub-scales for the month of June. An inspection of the mean scores indicated that females reported higher levels of anxiety than males. However, only Interpretation anxiety sub-scale was statistically significant. Indicating that females experienced higher level of interpretation anxiety than males.

Table 4.29: Descriptive statistics for gender difference for June administration.

	Mean	SD	MD	F	p-value
Test and Class Anxiety			0.172	0.935	0.336
Male	3.111	0.804			
Female	3.283	0.982			
Interpretation Anxiety			0.346	5.331	0.023*
Male	2.673	0.748			
Female	3.019	0.769			
Fear of Asking for Help			0.158	0.672	0.414
Male	3.135	0.891			
Female	3.293	1.047			
Worth of Statistics			0.058	0.130	0.720
Male	2.608	0.782			
Female	2.666	0.870			
Fear of the Teacher			0.018	0.010	0.919
Male	2.435	0.831			
Female	2.453	0.942			
Computation Self-concept			0.13	0.508	0.478
Male	2.590	0.868			
Female	2.720	0.978			

* Significant at the 5% level
Note: SD= Standard deviation, MD= Mean difference (Female - Male)

Table 4.30 presents the Box's test of equality of covariance matrices to check the assumption of homogeneity of covariance across the groups. The null hypothesis for this test is that the observed covariance matrices for the dependent variables are equal across the groups. The Box's M test (19.786) was not significant, p-value (0.615) $> \alpha$ (0.05). Indicating that there are no significant differences between the covariance matrices. Therefore, the assumption is not violated and Wilk's Lambda is an appropriate test to use.

Table 4.30: Box's test for Equality

Box's M	19.786
F	0.882
df 1	21
df 2	37244.40
p-value	0.615

Table 4.31 presents the results for multivariate analysis of variance. Six anxiety sub-scales were dependent variables for the month of June. The independent variable was gender. There was no statistically significant difference between males and females for the month of June on the combined dependent variables, F = [1.141]; p-value = [0.345]; Wilk's Lambda = [0.933]; partial eta squared = [0.067].

Table 4.31: Multivariate tests for the six anxiety sub-scales in June.

Effect		Value	F	H_0 df	Error df	P-value
Gender	Pillai's Trace	0.067	1.141	6	96	0.345
	Wilk's Lambda	0.933	1.141	6	96	0.345
	Hotelling-Lawley Trace	0.071	1.141	6	96	0.345
	Roy's Largest Root	0.071	1.141	6	96	0.345

* Significant at the 5% level

4.6 Correlation Analysis

To further investigate the properties of the data, correlation analysis was conducted to the three sections of STARS and to the six anxiety sub-scales of STARS over the three administrations. The correlation coefficient (r) represents the strength of association between two variables by means of a number ranging from -1 to +1, it measures the linear relationship between variables. r=1 indicates a perfect positive relationship, while r=-1 indicates a perfect negative correlation. A value of 0 (zero) indicates that there is no association between the two variables. A value greater than 0 (zero) indicates a positive association; that is, as the value of one variable increases, so does the value of the other variable. A value less than 0 (zero) indicates a negative association; that is, as the value of one variable increases, the value of the other variable decreases. Preliminary assumption testing was conducted to check level of measurement, bivariate normally distributed with no serious violations noted. Therefore, **Pearson's product-moment correlation** was used to determine the correlations between variables and measure the linear relationship between variables.

4.6.1 Correlation between three sections of STARS.

Table 4.32 presents correlation coefficients between Anxiety toward Statistics for the three Administrations. Significant and moderate positive correlations existed between Anxiety toward Statistics in February and March (r=0.243) and in March and June (r=0.435). No significant correlation existed between Anxiety toward Statistics in February and June. These results indicates that the higher the level of anxiety, the more anxious students become toward statistics.

Table 4.32: Pearson correlation between Anxiety toward Statistics for the three administrations

		Anxiety toward Statistics (February)	Anxiety toward Statistics (March)
Anxiety toward Statistics (March)	Pearson correlation	0.243*	
	p-value	0.013	
Anxiety toward Statistics (June)	Pearson correlation	0.140	0.435*
	p-value	0.159	0.000

* Significant at the 5% level

Table 4.33 presents correlation coefficients between Attitude toward Statistics for the three Administrations. Pearson correlation suggested a moderate and significant positive association between the three Attitude toward Statistics from three different administrations. These results indicates that the higher the level of attitude, the more negative attitude students toward statistics.

Table 4.33: Pearson correlation between Attitude toward Statistics for the three administrations

		Attitude toward Statistics (February)	Attitude toward Statistics (March)
Attitude toward Statistics (March)	Pearson correlation	0.571*	
	p-value	0.000	
Attitude toward Statistics (June)	Pearson correlation	0.483*	0.589*
	p-value	0.000	0.000

* Significant at the 5% level

Table 4.34 provides correlation coefficients between Mathematics Self-concept for the three Administrations. Significant but weak positive correlation was observed between Mathematics Self-concept for all three administrations.

Table 4.34: Pearson correlation between Mathematics Self-concept for the three administrations

		Mathematics Self-concept (February)	Mathematics Self-concept (March)
Mathematics Self-concept (March)	Pearson correlation	0.424*	
	p-value	0.000	
Mathematics Self-concept (June)	Pearson correlation	0.297*	0.300*
	p-value	0.002	0.002

* Significant at the 5% level

Table 4.35 presents correlation between average of the three sections of STARS. There was a significant and weak positive correlation between Anxiety toward Statistics and Attitude toward Statistics, indicating that, the higher the levels of anxiety, the higher the levels of attitude. On the other hand, Pearson correlation stated negative and weak correlation between Mathematics Self-concept, Anxiety toward

Statistics and Attitude toward Statistics, however, the two correlations were not significant.

Table 4.35: Pearson correlation between average scores of the STARS three sections

		Anxiety toward Statistics	Attitude toward Statistics
Attitude toward Statistics	Correlation	0.447*	
	p-value	0.000	
Mathematics Self-concept	Correlation	-0.159	-0.071
	p-value	0.109	0.476

* Significant at the 5% level

4.6.2 Correlation between six anxiety sub-scales.

To further investigate the properties of the STARS questionnaire. Correlation analysis was conducted on the six anxiety sub-scales for each of the three administrations. As a means of checking multicollinearity, the correlation (between the dependent variables) should be low to moderate. If the correlation is 0.60 or above there exist signs of multicollinearity. The circled correlation coefficients in this section indicates signs of multicollinearity. Therefore, anxiety sub-scales will be tested by Variance Inflation Factors and Tolerance in section 2.7 to check multicollinearity. If there exist multicollinearity between the six sub-scales, the ones with high multicollinearity (VIF $>$ 5) will be eliminated.

Table 4.36 presents the Pearson correlation coefficients between the six anxiety sub-scales for the month of February. Significant positive correlations were found among all six sub-scales. Most notably, Test and Class Anxiety was strongly and positively correlated to Fear of Asking for Help. In addition, Worth of Statistics is strongly and positively correlated to both Fear of the Teacher and Computation Self-concept.

Table 4.36: STARS six anxiety sub-scales correlations for the month of February

		Test and Class Anxiety	Interpretation Anxiety	Fear of Asking for Help	Worth of Statistics	Fear of Teacher
Interpretation Anxiety	Pearson correlation	0.428*				
	p-value	0.001				
Fear Asking for Help	Pearson correlation	0.931*	0.347*			
	p-value	0.000	0.010			
Worth of Statistics	Pearson correlation	0.351*	0.197	0.291*		
	p-value	0.002	0.305	0.011		
Fear of the Teacher	Pearson correlation	0.277*	0.253*	0.241*	0.656*	
	p-value	0.006	0.010	0.014	0.000	
Computation Self-concept	Pearson correlation	0.332*	0.218*	0.290*	0.719*	0.561*
	p-value	0.001	0.027	0.003	0.000	0.000

* Significant at the 5% level

Table 4.37 presents the Pearson correlation coefficients between the six anxiety sub-scales for the month of March. Significant positive correlations were found among all six sub-scales. Most notably, Test and Class Anxiety was strongly and positively correlated to Fear of Asking for Help. In addition, Worth of Statistics is strongly and positively correlated to both Fear of the Teacher and Computation Self-concept.

Table 4.37: STARS six anxiety sub-scales correlation for the month of March

		Test and Class Anxiety	Interpretation Anxiety	Fear of Asking for Help	Worth of Statistics	Fear of Teacher
Interpretation Anxiety	Pearson correlation	0.502*				
	p-value	0.000				
Fear Asking for Help	Pearson correlation	$\boxed{0.926*}$	0.383*			
	p-value	0.000	0.000			
Worth of Statistics	Pearson correlation	0.401*	0.275*	0.382*		
	p-value	0.000	0.005	0.000		
Fear of the Teacher	Pearson correlation	0.427*	0.462*	0.385*	$\boxed{0.619*}$	
	p-value	0.000	0.000	0.000	0.000	
Computation Self-concept	Pearson correlation	0.386*	0.300*	0.398*	$\boxed{0.711*}$	0.510*
	p-value	0.000	0.002	0.000	0.000	0.000

* Significant at the 5% level

Table 4.38 presents the correlation coefficients between the six anxiety sub-scales for the month of June. Significantly positive correlations were found among all six sub-scales for the month of June. Some correlations were much stronger than that of the first and second administrations. Most notably, Test and Class Anxiety was strongly and positively correlated to Interpretation Anxiety and Fear of Asking for Help. In addition, Worth of Statistics is strongly and positively correlated to both Fear of the Teacher and Computation Self-concept. Lastly, there exist strong and positive correlation between Fear of the Teacher and Computation Self-concept.

Table 4.38: STARS six anxiety sub-scales correlation for the month of June

		Test and Class Anxiety	Interpretation Anxiety	Fear of Asking for Help	Worth of Statistics	Fear of Teacher
Interpretation Anxiety	Pearson correlation	0.661*				
	p-value	0.000				
Fear Asking for Help	Pearson correlation	0.975*	0.639*			
	p-value	0.000	0.000			
Worth of Statistics	Pearson correlation	0.340*	0.248*	0.368*		
	p-value	0.000	0.012	0.000		
Fear of the Teacher	Pearson correlation	0256*	0.259*	0.301*	0.772*	
	p-value	0.009	0.008	0.002	0.000	
Computation Self-concept	Pearson correlation	0.390*	0.286*	0.431*	0.889*	0.712*
	p-value	0.000	0.006	0.008	0.000	0.000

* Significant at the 5% level

Table 4.39 presents the Pearson correlation coefficients between average scores of the six anxiety sub-scales. Significant positive correlations were found among all six sub-scales. Most notably, Test and Class Anxiety was strongly and positively correlated to Fear of Asking for Help. In addition, Worth of Statistics is strongly and positively correlated to both Fear of the Teacher and Computation Self-concept. Lastly, There was a strongly positive correlation between Fear of the Teacher and Computation Self-concept.

Table 4.39: Pearson correlation of average scores of six anxiety sub-scales

		Test and Class Anxiety	Interpretation Anxiety	Fear of Asking for Help	Worth of Statistics	Fear of Teacher
Interpretation Anxiety	Pearson correlation	0.555*				
	p-value	0.000				
Fear Asking for Help	Pearson correlation	0.953*	0.466*			
	p-value	0.000	0.000			
Worth of Statistics	Pearson correlation	0.423*	0.288*	0.426*		
	p-value	0.000	0.003	0.000		
Fear of the Teacher	Pearson correlation	0.359*	0.394*	0.364*	0.791*	
	p-value	0.000	0.000	0.001	0.000	
Computation Self-concept	Pearson correlation	0.403*	0.436*	0.436*	0.845*	0.710*
	p-value	0.000	0.000	0.001	0.000	0.000

* Significant at the 5% level

4.6.3 Summary: correlation analysis

To summarise, significantly positive correlations were found between all three sections of STARS. These results indicates that the higher the level of anxiety or attitude, the more students become anxious and the more they have negative attitude toward statistics. Most notable is that Test and Class Anxiety and Fear of Asking for Help were strongly and positively correlated throughout the semester. In addition, Worth of Statistics was highly and positively correlated to Computation Self-concept in all three administrations. Fear of the Teacher was highly and positively related to Computation Self-concept and Worth of Statistics. From the correlation matrix alone we cannot conclude on the absence of multicollinearity. To test for multicollinearity Tolerance and Variance Inflation Factors are considered.

4.7 Test of Multicollinearity

There are number of potential statistical problems with any regression models. These problems include perfect multicollinearity. The presence of multicollinearity can result in distorted regression results. Multicollinearity is a statistical phenomenon in which two or more independent variables in a classical multiple linear regression model are heavily related (Bowerman and O'connell, 1990). Two variables exhibit complete collinearity if their correlation coefficient is 1 and complete lack of collinearity if their correlation coefficient is 0 (Wheeler and Tiefelsdorf, 2005).

The presence of multicollinearity increases the standard errors of the estimated regression coefficients (Wheeler and Tiefelsdorf, 2005). This makes it difficult to obtain accurate estimates of the individual effects of the independent variables, hence reducing the degree of confidence that one can place in the coefficient estimates values. It becomes difficult to assess the individual effects because the estimated regression coefficient values have dubious interpretation (Bowerman and O'connell, 1990). Incorrect conclusions are drawn about the effect of the independent variables on the model. Thus, multicollinearity must be eliminated or at least reduced.

The variance inflation factor (VIF) is used to detect whether one predictor has a strong linear association with remaining predictors (the presence of multicollinearity). Lazaridis and Tryfonidis (2006) explain that the VIF measures how much of the variance of an estimated regression coefficient increases if the predictors are correlated. Montgomery et al. (2015) suggest that when the VIF is greater than 5 (VIF>5), then the regression coefficients maybe poorly estimated. In this study we used the VIF and Tolerance commands when regressing performance against the explanatory variables. The predictors had resultant variance inflation factor ranging between 1.276 and 1.250 across the model specification as shown in Table 4.40. The results indicates that there is absence of multicollinearity between three sections of STARS in the regression model.

Table 4.40: Multicollinearity test for the three sections of STARS

Model	Coefficient	S.E	t-value	p-value	Tolerance	VIF
Anxiety toward Statistics	-2.37	2.26	-1.050	0.296	0.784	1.276
Attitude toward Statistics	-2.99	2.07	-1.442	0.152	0.800	1.250
Mathematics Self-concept	7.27	3.54	2.054	0.043*	0.975	1.026

* Significant at the 5% level

Table 4.41 presents the multicollinearity for the six anxiety sub-scales. Considering the relationships between the independent variables (six anxiety sub-scales) it was necessary to investigate the data for multicollinearity before regression and path analysis was run. For the six anxiety sub-scales, multicollinearity was evaluated first with the Pearson correlation coefficient. The Pearson product-moment correlations for the six anxiety sub-scales are presented in section 4.6.1. Test and Class Anxiety was observed to be highly correlated with Fear of Asking for Help, and resulted in a VIF of 13.854, indicating multicollinearity. In this case, Test and Class Anxiety will be dropped as the result of high VIF.

Table 4.41: Multicollinearity test for the six STARS anxiety sub-scales

Model	Coefficient	S.E	t-value	p-value	Tolerance	VIF
Test and Class Anxiety	-0.483	6.703	-0.072	0.943	0.072	13.854
Interpretation Anxiety	1.581	2.958	0.535	0.594	0.571	1.753
Fear of Asking for Help	-2.878	5.598	-0.514	0.608	0.080	12.450
Worth of Statistics	0.636	4.016	0.158	0.874	0.198	5.055
Fear of the Teacher	3.490	3.188	1.095	0.276	0.333	3.005
Computation Self-concept	-6.219	3.049	-2.039	0.044*	0.264	3.794

* Significant at the 5% level

Table 4.42 presents reduced multicollinearity test for the reduced anxiety sub-scales. There was still high correlation between Worth of Statistics and Fear of the Teacher with Computation Self-concept. The VIF of Worth of Statistics was however 5.001. As a result of the fact that the VIF was greater than 5, the decision was made to omit Worth of Statistics from the list of variables that may be used in the regression model and path analysis.

Table 4.42: Reduced multicollinearity test for the six STARS anxiety sub-scales

Model	Coefficient	S.E	t-value	p-value	Tolerance	VIF
Interpretation Anxiety	1.487	2.643	0.563	0.575	0.707	1.414
Fear of Asking for Help	-3.257	1.921	-1.696	0.093	0.676	1.480
Worth of Statistics	0.574	3.902	0.147	0.883	0.196	5.001
Fear of the Teacher	3.517	3.149	1.117	0.267	0.338	2.963
Computation Self-concept	-6.175	2.973	-2.077	0.040*	0.274	3.644

* Significant at the 5% level

Table 4.43 present final variables of anxiety sub-scales on multicollinearity. The results showed low to medium strength correlations. The predictors had resultant variance inflation factor ranging 1.385 and 2.198 across the model specification as shown in Table 4.43. Therefore, the results indicates absence of multicollinearity between anxiety sub-scales.

Table 4.43: Final multicollinearity test for the six STARS anxiety sub-scales

Model	Coefficient	S.E	t-value	p-value	Tolerance	VIF
Interpretation Anxiety	1.432	2.603	0.550	0.584	0.722	1.385
Fear of Asking for Help	-3.217	1.892	-1.700	0.092	0.689	1.452
Fear of the Teacher	3.756	2.686	1.398	0.162	0.459	2.177
Computation Self-concept	-5.899	2.298	-2.568	0.012*	0.455	2.198

* Significant at the 5% level

4.8 Regression Analysis

This section presents the regression (univariate and multivariate analysis) output in respect of the relationship between average performance, average of three the sections of STARS and average of the different anxiety sub-scales. Regression analysis is an analysis technique that assesses whether one or more predictor variables explain the dependent variable. The following assumptions are required for normal linear regression based on ordinary least squares.

- Linear relationship
- Multivariate normality
- No or little multicollinearity
- No auto-correlation
- Homoscedasticity

The R^2 statistic in each regression output measures how well the proposed regression model (containing the explanatory variables) actually fits the data or how much of the variation in the dependent variable is explained by the variation in the independent variable(s). It is also known as the coefficient of determination, or the coefficient of multiple determinations for multiple regression. The closer the figure of R-squared gets to 1 the more variation explained. The standard error indicates sampling variability of the regression (Brooks et al., 2008). The t-test tests single hypotheses involving only one coefficient, the F-statistic tests more than one coefficient simultaneously. The significance of the F-statistic produced by the regression outputs indicates that there is a linear relationship between the dependent and the set of independent variables. In these models, average Performance is the dependent variable and the average of the three sections of STARS and six anxiety sub-scales are the independent variables.

4.8.1 Multivariate Analysis: Multiple Linear Regression

According to Katzenellenbogen et al. (1997), multiple regression analysis consists of a range of statistical techniques which, on the basis of mathematical models, can evaluate the inter-relationship of more than two variables. Therefore, the effect of a variable on a response variable can be determined while being adjusted for the effect of other variables. To be able to investigate the more complicated sets of variables and the confounding effect of the variables, it is necessary to complete the study by using analysis known as multiple regression (Pagano et al., 2000; De Klerk, 2011).

Table 4.44 summarises the multivariate analysis results for the three sections of STARS. The test was conducted at a 5% significance level thus all p-values greater than 0.05 represent non-significant variables. From Table 4.44, the only significant variable is Mathematics Self-concept. The output shows an R^2 0f 10.3%, meaning the model fits the data marginally. The R^2 value was low which means that there are other factors which explains and affect the students' performance. The R^2 for this model indicates that the variation of the independent variables explained 10.3% of the variation of the students' performance. The results show a weak relationship between performance and three sections of STARS.

Table 4.44: Multivariate analysis between average Performance and three sections of STARS

		Univariate		**Multivariate**			
Dependent variable	Independent variable	Coeff	p-value	Coeff	S.E	t-value	p-value
Performance	Anxiety toward Statistics	-4.48	0.031*	-2.372	2.258	-1.050	0.296
	Attitude toward Statistics	-4.24	0.027*	-2.985	2.070	-1.442	0.152
	Mathematics Self-concept	8.33	0.021*	7.273	3.541	2.054	0.043*

* Significant at the 5% level

Table 4.45 summarises the multivariate analysis results for the four anxiety sub-scales. The test was conducted at a 5% significance level thus all p-values greater than 0.05 represent non-significant variables. Two anxiety sub-scales were eliminated from six anxiety sub-scales as a result of multicollinearity, see Table 4.43. From Table 4.45, the only significant variable is Computation Self-concept. The output shows an R^2 0f 12.7%, meaning the model fits the data marginally. The R^2 value was low which means that there are other factors which explains and affect the students' performance. The R^2 for this model indicates that the variation of the independent variables explained 12.7% of the variation of the students' performance. The results show a weak relationship between performance and four anxiety sub-scales.

Table 4.45: Multivariate analysis between average Performance and anxiety subscales

		Univariate		Multivariate			
Dependent variable	Independent variable	Coeff	p-value	Coeff	SE	t-value	p-value
Performance	Interpretation Anxiety	-1.50	0.521	1.432	2.603	0.550	0.584
	Fear of Asking for Help	-4.17	0.011*	-3.217	1.892	-1.700	0.092
	Fear of the Teacher	-2.08	0.279	3.756	2.686	1.398	0.165
	Computation Self-concept	-4.69	0.003*	-5.90	2.298	-2.568	0.012*

* Significant at the 5% level

4.9 Path Analysis

Path analysis is an approach used to test theoretical models that specify the causal relationships between a number of observed variables. It determines whether the theoretical model, as often found in practice for different disciplines, successfully accounts for the actual relationships observed in the sample data (O'Rourke and Hatcher, 2013). Path analyses were conducted to test the model. In effect a path analysis is an extension of a regression analyses as it is used to test the fit of the correlation matrix.

4.9.1 Saturated Model: Three sections of STARS

Path modelling allows one to model the interrelationship between the explanatory variables as well as with the dependent variable. In order to investigate the effects of Anxiety toward Statistics, Attitude toward Statistics and Mathematics Self-concept on Students' Performance, path modelling was conducted. Table 4.46 presents the effects of three sections of STARS on performance. The test was conducted at a 5% level of significance thus all p-values greater than 0.05 represent non-significant variables. The only significant variable is Mathematics Self-concept. The results indicates that, according to this mode, Mathematics Self-concept directly affects Students' Performance.

Table 4.46: Effects of three sections of STARS on average performance

Model	Coeff	S.E	t-value	p-value
Performance <— Anxiety toward Statistics	-2.37	2.22	-1.066	0.286
Performance <— Attitude toward Statistics	-3.00	2.04	-1.464	0.143
Performance <— Mathematics Self-concept	7.27	3.49	2.085	0.037*

* Significant at the 5% level

The revised model at 5% level of significance would be:

Performance = 55.12 - 2.37(Anxiety toward Statistics) - 3.00(Attitude toward Statistics) + 7.27(Mathematics Self-concept) + ε

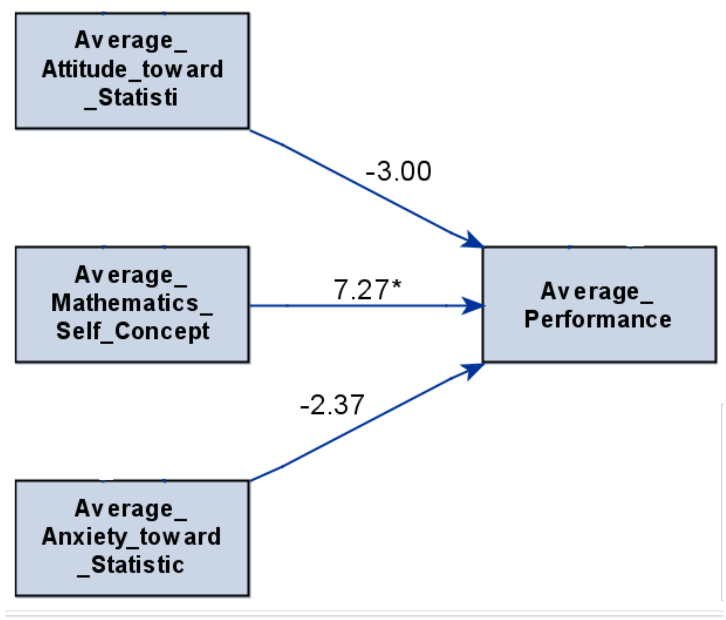


Figure 4.7: Saturated path modelling analysis for the three sections of STARS

4.9.2 Reduced Model: Two sections of STARS

Reduced model was produced by removing the highly insignificant variables from the saturated model. From Table 4.46 two sections of STARS, namely, Attitude toward Statistics and Anxiety toward Statistics were insignificant. Anxiety toward Statistics was omitted from the model because it was highly insignificant. Table 4.47 presents the effects of two sections of STARS on performance. The two sections of STARS were statistically significant in the reduced model. Mathematics self-concept presents a significant and positive coefficient, which indicates that the higher the Mathematics Self-concept the higher the students' performance. Attitude toward Statistics presents a significantly negative coefficient, which indicates that, the higher the Attitude of students toward statistics the lower the performance.

Table 4.47: Effects of two sections of STARS on average performance

Model	Coeff	S.E	t-value	p-value
Performance <— Attitude toward Statistics	-3.97	1.839	-2.147	0.0318*
Performance <— Mathematics Self-concept	7.79	3.472	2.248	0.025*

* Significant at the 5% level

The revised model at 5% level of significance would be:

Performance = 48.623 - 3.97(Attitude toward Statistics) + 7.79(Mathematics Self-concept) $+ \varepsilon$

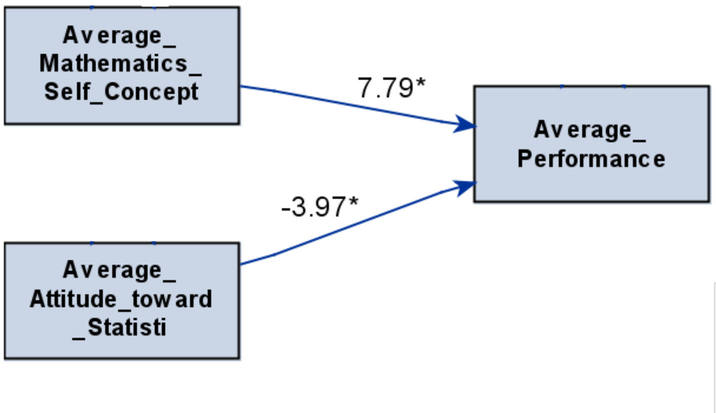


Figure 4.8: Reduced path modelling analysis for the three sections of STARS

4.9.3 Saturated Model: Anxiety sub-scales

In predicting performance with regard to anxiety sub-scales, the proposed conceptual model was analysed by path modelling. In this model, as the result of assumption of multicollinearity, four sub-scales will be used to test their effects on performance. Table 4.48 presents effects of anxiety sub-scales on performance, not all anxiety sub-scales are significantly associated with performance. Computation Self-concept significantly and negatively influence performance. Computation Self-concept observed a statistically, and negative coefficient, which indicated that the higher the computation anxiety, the lower the performance. The output shows $R^2 = 0.1263$ which indicates that the model fits the data marginally.

Table 4.48: Effects of four anxiety sub-scales on average performance

Model	Coeff	S.E	t-value	p-value
Performance <— Interpretation Anxiety	1.431	2.551	0.561	0.5747
Performance <— Fear of Asking for Help	-3.217	1.855	-1.734	0.0828
Performance <— Fear of the Teacher	3.756	2.632	1.427	0.1537
Performance <— Computation Self-concept	-5.899	2.252	-2.619	0.009*

* Significant at the 5% level

The revised model at 5% level of significance would be:

Performance = 68.78 + 1.431(Interpretation Anxiety) - 3.22(Fear of Asking for Help) + 3.76(Fear of the Teacher) - 5.90(Computation Self-concept) + ε

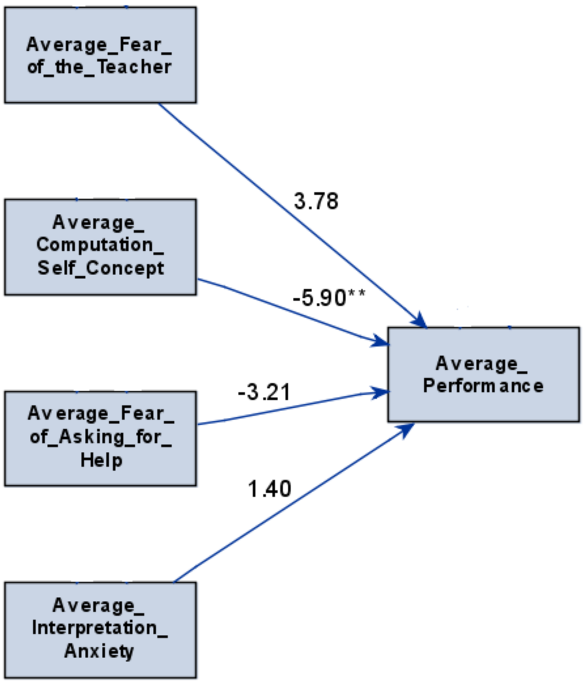


Figure 4.9: Saturated path modelling analysis for the anxiety sub-scales

4.9.4 Reduced Model: Anxiety sub-scales

Interpretation Anxiety was removed from the proposed theoretical model and the model was re-evaluated. The reduced model for the effects of anxiety sub-scales on performance provided same results from the saturated model, as Computation Self-concept become the only significant variable after Interpretation Anxiety was eliminated in the model. Table 4.49 presents the effects of anxiety sub-scales on performance. Computation Self-concept has a negative and significant coefficient, which indicates that Computation Self-concept negatively affect performance.

Table 4.49: Effects of three anxiety sub-scales on average performance

Model	Coeff	S.E	t-value	p-value
Performance <— Fear of Asking for Help	-2.822	1.719	-1.642	0.1006
Performance <— Fear of the Teacher	4.119	2.556	1.611	0.1071
Performance <— Computation self-concept	-5.977	2.251	-2.655	0.0079*

* Significant at the 5% level

The revised model at 5% level of significance would be:

Performance = 71.06 - 2.82(Fear of Asking for Help) + 4.12(Fear of the Teacher) - 5.98(Computation Self-concept) + ε

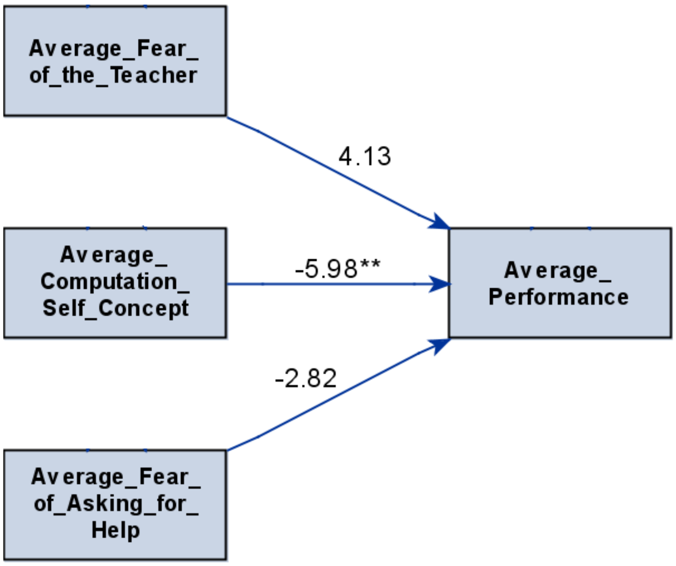


Figure 4.10: Reduced path modelling analysis for the anxiety sub-scales

To summarise, structural equation modelling was utilised to evaluate the results relating to the process or paths depicting the variables influencing students' performance.The path analysis indicates that performance is partially or slightly influenced by Attitude toward Statistics, Mathematics Self-concept and Computation Self-concept. However, students who had high level of Mathematics Self-concept reported lower levels of statistics anxiety but with an increasing performance. According to Diaz et al. (2001) these students are more likely to be interested in statistics, to deploy higher skills in mathematics, and to invest more time effort on the subject.

4.10 Analysis of Qualitative data

In this section, findings related to the interviews are discussed. The interviews were conducted with six students and each participant was interviewed individually. The purpose of the interviews was to provide an understanding of introductory statistics students' experiences and perceptions of statistics anxiety and attitude toward statistics. In particular, the aim of the interviews was to identify factors that may cause or reduce their statistics anxiety levels, to determine whether statistics anxiety had any influence on their performance, whether students experienced any physiological symptoms and whether the mathematics involved in the course had any influence on their anxiety. Findings are presented in the following sections.

4.10.1 Do you like statistics? Why/ Why not?

In response to the first question, three students stated that they like and enjoy statistics. The other two participants stated that they do not like statistics. One respondent was ambiguous about his attitude toward statistics because he thought that he understands statistics but only to find that he struggles with tutorials, tests and examination. The following comments reflect this:

- *Yes I like statistics. When I get stuff right and do well in statistics, it motivates me to do well in other subjects because statistics is difficult to understand.*

Therefore it makes me more confident in other subjects.

- *Statistics is fine. I like it to work out equations and when I find them successful it is nice, but if I struggle I do feel anxious so much that I feel that I won't complete my task, but statistics is better than other subjects.*
- *I like Statistics, for one reason, because it helps us on how to approach different challenges in life as most of life and business problems are statistically based.*
- *No I don't. I don't think I am inclined to do Mathematics. I like to do things and to learn something, but I don't really understand statistics. Maybe I don't like statistics because I don't understand it. One usually like things more if you understand it better. Because I don't like statistics, I do not give much attention to it and then I fall behind.*
- *I hate anything that has to do with numerical values. I don't like mathematics and I don't like numbers.*
- *I am average at that one, because sometimes statistics gives me problems. I would think I understand but when I am alone doing my tutorials I struggle with most of the problems asked, even during the tests and examination I mostly discover that I have a problem in understanding statistics because of disappointing marks.*

4.10.2 Was it difficult for you to learn statistics?

Four of the participants stated that they struggled to learn statistics. The other two respondents indicated that they did not struggle at all in learning statistics because they had a good mathematical background. In addition, these two participants commented that the materials were excellent and that it made the learning of statistics much easier. The following statements reflect this:

- *Yes in the beginning. Sometimes I did found problems and topics I don't understand but mostly got help from my friends and group mates. But after receiving help statistics made sense to me.*

- *It was a bit challenging, because it was my first time learning it.*
- *Yes it was difficult. All the topics were actually difficult to learn and understand.*
- *Yes it was really difficult. Because it takes a lot of time to practice and to perfect. And the topics are all at a very high level to me and it is so difficult for me.*
- *No. Firstly, I am a very mathematics oriented person and I have a strong mathematics background. The study materials given were very good and helpful and I didn't struggle much to learn statistics.*
- *Not at all. On my side, given the materials, the well explained and detailed textbook, I did enjoy the module. The lectures were very approachable in consultation times and during class.*

4.10.3 What do you believe is statistics anxiety?

The following statements reflect what students believed about statistics anxiety:

- *Statistics anxiety is when you are anxious and worry about what is going to happen in statistics. Statistics anxiety for me is when I struggle with statistics and being anxious because I feel like I am falling behind.*
- *I think it is when you feel that you don't have any power of what is going to happen because you feel you should have done more.*
- *It is a state of worry when you face statistics problems, test, assignment or examination in statistics.*

4.10.4 What was your attitude toward and anxiety about statistics in the beginning of the year? Did it change during the course of the semester?

Four of the participants voiced a negative attitude toward statistics. The other two stated that they had a positive attitude toward statistics. One participant stated that his attitude was positive and contributed positively toward his performance. On the other hand, all but one of the participants stated that their attitude changed throughout the semester and that their level of anxiety increased as the result of difficulty of topics, tutorials, tests and examination. Two students commented that they did not look forward going to classes or even did not attend classes because of their anxiety. Two students voiced that they did not experience anxiety, because of a good mathematics background and one student already did statistics during his previous qualification. Their opinions are illustrated with the following quotes:

- *I was open-minded because I never did statistics before, but I was little sceptical about how things are going to happen, how is the lecture going to be like and, after my first class my scepticism changed and I felt better after some weeks. But I was still anxious toward the end of the semester because I performed well in the first test and badly in the examination. My anxiety before the exam was extremely high, especially with the financial part of statistics.*

- *No, I have a good mathematical background, I was very confident in mathematics and other numeric oriented subjects and I didn't struggle with statistics. I had a positive attitude toward statistics at the beginning, but as statistics got difficult I become more anxious and my attitude sort of changed. But my anxiety contributed positively toward my performance because it made me work harder and performed better.*

- *I had a negative attitude toward statistics in the beginning of the year because I did not know what it was all about. During the first three weeks I knew that statistics was not for me and I did not look forward to the classes.*

- *I wasn't positive at all because I did not like it. It really influenced me not to go to classes and I mostly skipped classes. I was anxious all the time when I am facing statistics. My anxiety was very high during the tests and examination.*
- *My attitude was good and positive because I told myself I would promote statistics in order not to write the examination. My attitude changed during the semester especially when I saw that my grades were low and had to write the examination in the end.*
- *My attitude toward statistics was very negative due to challenges that I have already mentioned. Actually I was very negative because of the mathematics, and because the matter of failing brings the negative attitude toward a subject.*

4.10.5 Do you think that the fact that you were anxious had any effect on your performance?

All six participants voiced that their anxiety had an effect on their performance. Two of the respondents stated that their anxiousness motivated them to work hard and get good marks, while other respondents indicated that their anxiety made them worry about the future and what is going to happen if they fail. Their opinions are illustrated with the following quotes:

- *Yes, because it pushed me to do better and do well in statistics. I knew it was going to be hard for me, as mathematics is not my strong point. My anxiousness pushed me to perform and do better. And it had a positive impact on my first test because it helped me to perform, but my anxiety had a very negative impact on my exam because I poorly performed in the examination.*
- *Yes, as I explained previously, the anxiety that I had about statistics was kind of motivating, so the stress and anxiousness pushed me to do better and work hard. The fact that I was anxious improved my marks. I did very well in Test 1 and in the examination.*

- *Yes definitely. The fact that I was negative and anxious definitely had an influence on my performance. Because I was negative about it, I postponed learning for statistical tests and the exam until the last minute. I did not do well in my tests and that made me feel more negative toward the course.*

- *Yes, when I am anxious I start to think of things that are out of the paper, like what is going to happen if I fail, what am I going to do next year, do I have to leave the university and my mind will be million miles away from what I have to do.*

- *Yes, because I thought of so many questions that when I fail statistics I might loose my bursary, or even repeat the module that I once passed at my previous qualification.*

- *Yes. It really did, because once you have a fear of a subject you are not going to perform to your full potential. Because you already have a negative attitude as I had a negative attitude, I had panics and I performed badly.*

4.10.6 Did you experience any physiological symptoms such as panic attack, heart racing or feeling scared when you do statistics or write the tests and exams?

Four of the participants mentioned that they did experience physiological symptoms such as panic attack, sweating and heart racing. This theme of physiological symptoms found is consistent with the findings of the research conducted by Onwuegbuzie et al. (1997). They found students reporting psychological symptoms such as depression, frustration, panic and worry, as well as physiological signs of headaches, muscle tension and feeling sick. However, two respondents did not experience any physiological symptoms. The following quotes describe the applicable students' physiological symptoms:

- *Yes definitely, I experienced sweating and heart racing.*

- *Yes, I did experienced heart racing, sweating and I worried a lot about the module.*
- *Yes, I did experienced heart racing though I knew I will pass the module.*
- *Yes I did, more heart racing, panics and sweating.*

4.10.7 What are the factors that increased your levels of anxiety?

During the interviews with the participants, many themes emerged that increased students level of anxiety: *Time constraint, mutual completion between classmates, translation of the study materials from English to Afrikaans, work capacity, mathematics in statistics* and *fear of asking for help.* The following comments in this regard confirm this:

- *Time constraint increased my anxiety because I struggled with time management.*
- *Fellow classmates sometimes made me more anxious because we did had this mutual competition between friends, so if they do better, I had to do better than them in the following test. Sometimes a lecture don't present* 100% *of all the topics and I have to learn it on my own and then if I struggle to understand it I felt more anxious. Another challenge that I had to face was the translation of the study material from English to Afrikaans.*
- *The only factor that increased my anxiety is when I was not competent to do the tutorials and assignments. I was fine with the interpretations, if I understand the work, and became more confident in doing the maths during the semester, although I still do not like mathematics and I can still not see where it can be applied.*

- *The lecturers were fine and they did their part exceptionally well, but the work capacity really made me more anxious. Also the mathematics in statistics really increased my level of anxiety.*

- *Seeing that things are not going the way I planned them, sort of increased my level of anxiety. Like I said earlier I had to do all means to pass.*

- *Fear of asking for help really increased my level of anxiety. My mathematics skills also contributed to my level of anxiety, because I was afraid to ask a lecture some things I don't understand. Time constraint in the tests and examination also contributed in increasing my level of anxiety.*

4.10.8 What are the factors that decreased your levels of anxiety?

One factor pointed out by many participants was that groups of friends working together and explaining the work to each other decreased their anxiety. They rather got help from friends than from lecturers and student-assistance. Most of them agreed that the lecturer was very friendly, thus decreasing their anxiety. However, it seems that the tutorial classes were not very helpful. Some quotes in this regard are:

- *My lecture was great, and she did helped me to calm. She was very patient with the class, and that helped to decrease my level of anxiety. The fact that I did well in Test 1 also helped to decrease my anxiety.*

- *Good marks really decreased my level of anxiety. My lecturer also contributed in decreasing my level of anxiety when she told us that statistics is easy. The study groups also decreased my level of anxiety.*

- *The more I understood the work, the less was my anxiety and then I got hope to do better. Anything that I achieved made me more positive. The tutorials did help to give me more confidence. If you get something right then you feel* *more confident. We are a group of friends who work together and by helping each other we understood the work better in the end. I did not actually attend the tutorial classes and did not ask the tutors or lecturer for help. If I need help, I rather asked my friends.*

- *I didn't do well in statistics, but the discussion groups helped me a lot and they decreased my level of anxiety because there was always a person who knew something I didn't know and helping each other really helped. The tutorials also contributed in decreasing my level of anxiety. But I did bad the day I asked help from tutors and they were not much helpful because they helped me to get to an answer but not helped me to understand. They were suppose to help me understand it myself. Lastly my lecture played a vital role in decreasing my level of anxiety because she did encourage us to do better and told us that statistics is easy to understand.*

- *My lecturer did play a major role in helping with the module and that decreased my level of anxiety, even my time management toward the exams for preparations did decrease my level of anxiety.*

- *I think my performance was one of them, because my performance increased from Test 1, to Test 2 to the examination and I felt more confident. But I did not go to practicals because the tutors did not really help me to understand the work. My lecturer also contributed in decreasing my level of anxiety.*

4.10.9 What do you think about the statistics teacher? Did he/she make you feel more anxious? Why?

All the participants responded positively towards their lecturer with most of them indicating that the lecturer was encouraging and that she was one reason their level of anxiety decreased. However, one participant stated that the lecturer did not always indicate where in the textbook they should start working during a lecture. Some quotes in this regard are:

- *No, not at all, she was of great help and she was friendly and patient. She even helped me beyond the course.*
- *The lecturer was very good. She went through examples with us, and showed us how the concept maybe asked and that sort of decreased our level of anxiety. But she did not focus on the theoretical work but practical work. And the gap did make me anxious.*
- *The lecturer did not always indicate where in the textbook we have to start working. Sometimes we had to go back and forth to find out where exactly we are. This is something she can work on in the future, because it's confusing the students. Otherwise there is nothing wrong with the lecturer. She is really good. Someone who likes statistics will definitely like the lecturer and the way she operates.*
- *I liked her, we really had a bond and connection with her. She made us feel like we are at home.*
- *Our lecturer was perfect and she was one of the reasons I want to do statistics in the future.*
- *My lecturer was always open and good. Even after class she will always stress a point that people who don't understand must consult. She was always approachable.*

4.10.10 Were you comfortable in doing the mathematics included in the statistics module?

Three of the respondents had a negative attitude toward mathematics in the statistics module. The other three participants had a positive attitude toward mathematics. Those who had negative feelings indicated that they are not comfortable doing mathematics because mathematics was either not their strong point or they did not like mathematics at all. The following comments in this regard confirm this:

- *I am now, but in the beginning I was not comfortable because mathematics is not my strong point.*
- *Yes I was confident in doing mathematics because I am good in mathematics.*
- *I was not very comfortable because I do not like mathematics. I'm not really afraid of mathematics because we are forced to do it, but in principle I don't like mathematics.*
- *No, I am not comfortable in doing it. But my skills did improve with time. But I am not comfortable in doing mathematics because I don't like it.*
- *For me, when I look at statistics I look at it as mathematics. I don't separate the two because what I noticed they work hand in hand, so since I enjoyed mathematics, I was really comfortable with statistics.*
- *Yes, I was, though it was a bit challenging. Since I saw that statistics is the same as mathematics, I had to make peace to do it. But before I didn't like mathematics.*

4.10.11 Did you ever feel inadequate to do statistics?

Three of the participants felt inadequate to do statistics in the beginning of the semester, but felt adequate to do statistics later in the semester, mainly because of the help of friends and doing the practicals. Only one participant never felt inadequate to do statistics. These opinions are illustrated with the following quotes:

- *There were a few times when I thought I wasn't going to make it, but my lecturer and friends helped me step by step and that also contributed to decrease my level of anxiety. I then felt more adequate to do statistics.*
- *Yes, sometimes when I did on-line tests and find them difficult to do I felt inadequate.*

- *Yes I did. If I sit down alone and do the statistics and I don't understand what is going on, then I felt inadequate. But when my friends explained it to me and I understood the work, then I felt adequate again, which also gave me a little bit more hope.*

- *Yes, because I don't feel like statistics is going to contribute to my future academic plans. Therefore I felt negative about statistics and inadequate to do it.*

- *Yes I did. In the beginning of the semester I did not know how to go on with the module. I struggled but as time goes on with more practicals I was confident with everything.*

- *I have never felt inadequate, because statistics is to be part of my life because of the major I am doing which is Investment Sciences. I will be doing statistics during the whole of my program.*

4.10.12 Did you ever feel like giving up statistics or rather do it at a later stage?

One of the themes present throughout the interview transcriptions was giving up statistics. All six participants indicated that they wanted to give up sometime during the course. Participants used certain expressions to voice that they wanted to give up: *statistics took me to a point where I felt like I should quit, I was so upset I really wanted to change my course, the marks were not deserving, wanted to run out of the exam* and *end up skipping classes.* However, none of the participants indicated that they rather wanted to do the statistics course at a later stage. These opinions are illustrated with the following quotes:

- *Yes, During my exam period.*

- *Yes I did. Statistics took me to a point where I felt like I should quit, because some work is extremely difficult, especially when your major is theoretical like mine.*

- *Yes I did, but I realised that I had to pull through, so I did not give up statistics.*
- *Yes, when the June results were due, I was so upset I really wanted to change my course.*
- *Yes, last semester I felt like giving up because the marks were not deserving especially when I knew I worked very hard. But I never gave up as statistics is important in everyday life.*
- *Yes, at the time when I was struggling a lot at the beginning of the semester. But later on I followed everything and I even thought I should continue doing statistics in the next year.*

4.10.13 Do you feel that statistics is a waste of time or does it make sense to you that you will use and apply it some or other time in the future?

In response to this question, five participants responded positively towards statistics, stating that statistics is not a waste of time because they are to use it in the future. Only one respondent stated that statistics is a waste of time. She indicated that she does not see where to use statistics in the future. The following comments in this regard confirm this:

- *I mostly use it because of what I am studying and yes, I will need it in the future. So no, statistics is not a waste of time at all.*
- *Personally, I feel that statistics is not a waste of time. It keeps my brain active because most of my subjects are read and repeat, thus they are mostly theoretical.*
- *No, I don't feel like statistics is a waste, somewhere and somehow it will be helpful in my career.*

- *No, it is not a waste at all. Like I said, it helped us to come up with our own strategies and concepts on how to deal with daily challenges on business issues and life in general. It makes a lot of sense to me.*

- *Yes, I feel it is a waste because I can't see where one can apply it in practice. Maybe if the lecturer shows us more practical applications, I will appreciate it more. There are a lot of students who does not understand why we have to study statistics. A lot of students feel it is a waste of time. The main thing is to show students where it can be applied some day.*

4.10.14 If you had a choice, would you do a statistics module or rather another non-mathematics module in its place?

Three of the participants voiced that they would rather take a non-mathematics module than a statistics module. The other participants preferred to do a statistics module. The following comments in this regard confirm this:

- *I think I will continue with statistics because I have developed a great passion and love for it.*

- *No I will definitely not continue with statistics. It is a great subject but it is not necessary for my major.*

- *I would probably not take statistics.*

- *Yes, I would love to do another module in the place of statistics.*

- *I think, I will do statistics, because if you understand it, you do well academically.*

- *No, I would go on with statistics.*

4.10.15 Analysis of qualitative responses

To summarise, statistics is an anxiety provoking subject for students. Not only because of the adverse effects on their outcomes, attitude, self-concept, and tendency to procrastinate, but also because it can affect students' decisions to enroll in statistics courses.

During the interviews the majority of the participants indicated high levels of anxiety toward statistics. Two of the students voiced that they do not like statistics because of the mathematics involved. Thus, they see statistics as a mathematics course. Other students indicated that they do enjoy statistics though they felt anxious about it during the semester. Four of the participants stated that they did struggled with statistics because it was their first time learning statistics. One student stated that statistics takes a lot of time to practice and to perfect and the topics were difficult to learn and understand.

Four of the participants voiced that their high statistics anxiety levels were due to their negative experiences in the past while taking mathematics courses, since mathematics and statistics are closely related fields. It was also observed that some students conceive statistics as mathematics. A few students stated that their attitude affected their performance positively because it forced them to work harder. The other students stated that their attitude toward statistics affected their performance negatively, though they passed.

Anxiety caused students to postpone learning for tests and examinations. However, most students were worried about their future if they were to fail statistics. Participants voiced factors that increased their statistics anxiety and among all points, *time constraints, work capacity, mathematics in statistics* and *fear of asking for help* resonated throughout the interviews. Students also stated factors that decreased their level of anxiety, for example, groups of friends working together and explaining the work to each other. They also stated that, they rather got help from friends than from lectures and student assistants, even though they were positive about the lecture and liked her very much.

All the participants responded positively toward their lecturer with most of them indicating that the lecturer was encouraging and that she was one reason their level of anxiety decreased. A similar point was raised by Williams (2010) and Malik (2015). Williams (2010) identified instructors as having an important influence on the anxiety levels experienced by students. Because of this identification, he suggested that instructors show students genuine concern for their feelings as well as their learning. Three of the participants felt inadequate to do statistics in the beginning of the semester. All the participants indicated that they wanted to give up sometime during the course. Anxiety toward statistics resonated throughout the interview. Most students expressed themselves with terms like: *panics, sweating, hearting racing, felt like crying and giving up.* Lastly, some of the participants voiced that they would rather take a non-mathematics module than a statistics module.

Table 4.50: Qualitative analysis summary results

Interview Questions	Yes	No
Do you like statistics?	3	3
Was it difficult for you to learn statistics?	4	2
Did your attitude change during the course of the semester?	5	1
Do you think that the fact that you were anxious had an effect on your performance?	6	0
Did you experience any physiological symptoms such as panic attack , heart racing or feeling scared when you do statistics or write the tests and exams?	4	2
Did your teacher make you feel more anxious?	0	6
Were you comfortable in doing the mathematics included in the statistics module?	3	3
Did you ever feel inadequate to do statistics?	3	3
Did you ever feel like giving up statistics or rather do it at a later stage?	6	0
Do you feel that statistics is a waste of time?	1	5
If you had a choice, would you do a statistics module?	3	3

Table 4.51 presents attitude of 6 students with regard to their experiences during and before the semester as part of the qualitative analysis.

Table 4.51: Attitude of Students toward Statistics

Participants	Q.1	Q.2	Q.4	Q.5	Q.7	Q.9	Q.10	Q.11	Q.12	Q.13	Q.14
1	+	+	+/-	+	+	+	+	+	-	+	+
2	+/-	-	+	+	+	+	+	-	-	+	-
3	+/-	-	-	-	+/-	-	-	+/-	-	+	-
4	-	-	-	-	-	+	-	-	-	-	-
5	-	+	+	-	+/-	+	+	+/-	-	-	+
6	+	+	-	-	+	+	+	+	-	+	+

Note: +: Positive attitude, -: Negative attitude, +/-: Positive and Negative attitude

4.11 Summary of Results

This chapter provides some insights of the relationship between three sections of Questionnaire (statistics anxiety, attitude toward statistics, mathematics self-concept), six anxiety sub-scales and performance over the course of the semester. The first part of the chapter provides descriptive statistics of students' levels of anxiety, attitude toward statistics and mathematics self-concept during the course of the semester. Changes in students' anxiety levels regarding the six anxiety sub-scales over the course of the semester were also reported. The second part of the chapter focuses on gender differences for the three sections of STARS and the six anxiety sub-scales. The third part of the chapter reported the association of statistics anxiety, attitude toward statistics, mathematics self-concept and the six anxiety sub-scales on performance in an introductory business statistics class. Correlation coefficients, univariate analysis (linear regression analyses), multivariate analyses (multiple regression analyses) and path modelling were conducted to determine whether significant relationships exist between the independent variables and average performance.

The last part of the chapter focuses on qualitative results regarding the interviews. According to the results in this chapter, this section endeavoured to provide answers to the hypotheses stated in chapter 3 (see section 3.1).

Table 4.52 presents the summary results for the quantitative analysis with the statistical methods utilised.

Table 4.52: Quantitative analysis summary results

Statistical tests	Three sections of STARS	Six anxiety sub-scales
Two-way MANOVA	Slight gender differences in February	Slight gender differences in February
One-way MANOVA: February	Non-significant gender difference	Significant gender difference
One-way MANOVA: March	Non-significant gender difference	Non-significant gender difference
One-way MANOVA: June	Non-significant gender difference	Non-significant gender difference
Paired t-test: February - March	Significant differences except Mathematics Self-concept	Significant difference for Worth of Statistics and Computation Self-concept
Paired t-test: March - June	Significant differences except Attitude toward Statistics	Non-significant differences
Paired t-test: February - June	Attitude toward Statistics was significantly different	Significant differences for Interpretation Anxiety, Worth of Statistics and Computation Self-concept
Pearson Correlation	Significant correlations except Mathematics Self-concept on Anxiety toward Statistics and Attitude toward Statistics.	Significant correlations
Multiple Regression	Mathematics Self-concept was significant	Computation Self-concept was significant
Path Analysis	Attitude toward Statistics and Mathematics Self-concept were significant	Computation Self-concept was significant

Hypothesis 1: No association between statistics anxiety, attitude toward statistics, mathematics self-concept and students' performance.

Anxiety toward Statistics was found to be positively correlated to Attitude toward Statistics (see Section 4.6). These results suggest that, an increase in anxiety caused an increase in attitude toward statistics and vice versa. However, Mathematics Self-concept was not significantly correlated with Anxiety toward Statistics as well as Attitude toward Statistics. Correlations between the six sub-scales for all three administrations were statistically significant and highly correlated. The results state that there is an association or relationship between the six anxiety sub-scales. What stands out, during the correlation results is that, Test and Class Anxiety and Fear of Asking for Help, Worth of Statistics and Fear of the Teacher, and Computation Self-concept, Fear of the Teacher and Computation Self-concept were highly correlated.

There was a significant univariate association between Anxiety toward Statistics, Attitude toward Statistics, Mathematics Self-concept and Performance. The output showed a low R^2, suggesting that there are other variables that highly affect students performance. In addition, there was a significant univariate association between Fear of Asking for Help, Computation Self-concept and Performance. Similarly, in these results, there is low R^2, suggesting that the four anxiety sub-scales fit the data marginally.

There was a significant multivariate association between Mathematics Self-concept and Performance but with low R^2. For every one unit increase in Mathematics Self-concept, there was a increase in Performance, Meaning there was a positive relationship between Mathematics Self-concept and Performance. There was a significant multivariate association between Computation Self-concept and Performance. According to Path Modelling analysis, Mathematics Self-concept had a significant and positive effect on Performance while Attitude toward Statistics had a significant negative effect on Performance. In addition, Computation Self-concept had a significant and negative effect on Performance.

Students with high level of Mathematics Self-concept are more likely to be interested in statistics, to deploy higher skills in Mathematics Self-concept, and to invest more time and effort on the subject (Diaz et al., 2001). This results align with those of Macher et al. (2012), Ali and Iqbal (2012) and Malik (2015). The qualitative analysis further proved the results as most student voiced that they were anxious at the beginning of the semester and they also indicated that their fear of statistics did affected their performance. The interviewed further stated that their anxiety affected their attitude toward statistics, also stating that their attitude changed throughout the semester as the result of their anxiety toward statistics. All participants voiced that their anxiety had an effect on their performance. However, some students stated that their anxiousness motivated them to work hard and get good marks. Other students become worried about their performance.

Hypothesis 2: Statistics anxiety, attitude toward statistics, mathematics self-concept and performance between males and females do not differ.

Multivariate analysis of variance was conducted to investigate gender differences for the three sections of STARS and Anxiety sub-scales. According to Wilk's Lambda test, no significant gender difference observed for the three sections of STARS (Anxiety toward Statistics, Attitude toward Statistics and Mathematics Self-concept) in three different administrations. MANOVA was also utilised to investigate gender difference for the six anxiety sub-scales. According to Wilk's Lambda test, there was no significant gender difference observed for all the three administrations. In qualitative analysis, most male students were confident with their knowledge of statistics and principles of mathematics except one who outlined that he hates anything that have to do with numerical or mathematical calculations.

Two-way MANOVA was conducted for both three sections of STARS and six anxiety sub-scales as dependent variables and gender with time as fixed factors (independent variables). The Pillai's Trace test was reported as a direct measure to test whether there are differences between the means of identified variables on a combination of dependent variables. No significant interaction found over and above main effects. The results indicated that there were no gender differences across the semester.

Hypothesis 3: Students' statistical anxiety, attitude toward statistics and mathematics self-concept, remains the same during the course of the semester.

Paired sample t-test results across the three administrations indicated that Anxiety toward Statistics between different pairs of administrations differed significantly except for the pair of February and June. This suggests that Anxiety toward Statistics did change through the semester. The difference in Attitude toward Statistics from February to March and from February to June was significantly different. This suggests that students developed a more negative attitude toward statistics during the semester. Mathematics Self-concept differed significantly from March to June. This suggest that students gained more confidence in doing mathematics toward the end of the semester.

Paired sample t-test results across the three administrations indicated that Test and Class Anxiety did not change or differ through the semester. Interpretation Anxiety was significantly different for the pair of February to June, indicating that it did changed from the month of February to June. Fear of Asking for Help and Fear of the Teacher did not differ significantly across the three pairs. The difference in Worth of Statistics and Computation Self-concept from February to March and from February to June were significantly different. This suggest that students developed high anxiety of these two anxiety sub-scales during the semester.

During the interviews most students indicated that there were factors which changed and influenced their attitude, anxiety and mathematics self-concept. Most of the participants indicated that they had a negative attitude toward statistics in the beginning of the semester and that their attitude became more negative during the semester due to difficulty of topics, tutorials, tests and the examination. Their negative attitude also increased their anxiety. Some students indicated that time constraint, translation of study materials, work capacity and inclusion of mathematics in the statistics module increased their level of anxiety. They even experienced psychological symptoms such as heart racing, panic and sweating. On the other hand, a few students did not experience any anxiety mainly because of a good mathematical background and a high mathematics self-concept.

Chapter 5 will focus on the conclusion, limitations and recommendations of the research study.

Chapter 5

Conclusion, Limitations and Recommendations

5.1 Introduction

The purpose of the study was to examine the association of statistics anxiety, attitude toward statistics and mathematics self-concept with regard to performance in an introductory statistics course. Specifically, the aim was to determine whether or not statistics anxiety affect students' performance. To accomplish these goals, data were collected by means of the STARS questionnaire and test and examination results were recorded. In addition, the study aimed to determine whether statistics anxiety differs by gender and to investigate the experiences and opinions of students regarding statistics anxiety. Qualitative information on the experiences and opinions of students regarding statistics anxiety and their attitude toward statistics were obtained by means of interviews.

Chapter 1 serves as a general introduction to the study. Chapter 2 discussed the research studies pertaining to statistics anxiety, its correlates and existing measurements thereof. The measurements included anxiety questionnaires and other instruments that measure anxiety. Chapter 3 focuses on the research design and methodology applied in the empirical investigation, while the results of the latter are presented and discussed in Chapter 4.

5.2 Conclusions from the literature review

The literature study revealed a lack of national research regarding statistics anxiety, attitude toward statistics and mathematics self-concept with relation to students' performance. International research, however indicates inconclusive results regarding the influence of statistics anxiety, attitude toward statistics and mathematics self-concept on performance. The findings that statistics anxiety may influence performance has been supported through research in multiple disciplines (Zeidner, 1991; Lalonde and Gardner, 1993; Onwuegbuzie and Seaman, 1995; Fitzgerald et al., 1996; Zanakis and Valenzi, 1997; Onwuegbuzie, 2000; Bell, 2008; Malik, 2015). These studies used the Statistics Anxiety Rating Scale (STARS) (Cruise et al., 1985).

In addition to statistics anxiety, previous research has examined student attitude toward statistics. Study attitude is a concept that is difficult to define and demarcate, but non-cognitive factors such as personality, self-esteem, self-efficacy, motivation, locus of control and health may be seen to collectively influence a student's attitude toward statistics. Therefore, attitude toward statistics and statistics anxiety were identified as independent variables that may have an influence on students' performance. Mills (2004) stated that students' attitudes toward statistics tend to be highly correlated with statistics anxiety. This relationship between anxiety and attitude was evidenced by Onwuegbuzie (2000) and Finney and Schraw (2003). The factors contributing to statistics anxiety are broad. Pan and Tang (2005) revealed four factors affecting statistics anxiety: fear of mathematics, lack of connection to daily life, pace of instruction, and attitude toward statistics. Gal and Ginsburg (1994) reported students often enter statistics courses with negative views or later develop negative feelings regarding the subject matter of statistics. The literature revealed that the higher an individual's level of anxiety the poorer the individual performed.

Statistics anxiety has been linked to mathematics self-concept in many research studies (Benson, 1989; Zeidner, 1991; Onwuegbuzie, 2000; Macher et al., 2012), indicating that students with poorer mathematics self-concept tend to have higher levels of statistics anxiety. Onwuegbuzie et al. (1997) reported that students with higher mathematics self-concept tend to have lower statistics anxiety. The findings between gender differences were established in the literature. Some research has indicated that females experience greater levels of statistical anxiety than males (Zeidner, 1991; Onwuegbuzie and Seaman, 1995; Papanastasiou and Zembylas, 2008; Baharun and Porter, 2009; Vahedi et al., 2011). Other research has found no gender differences in statistics anxiety (Onwuegbuzie, 2004; Lacasse and Chiocchio, 2005; Evans, 2007; Mji, 2009).

5.3 Conclusions from the empirical study

Chapter 4 focused primarily on looking at the data analysis and predictive models that can be used to develop prediction estimates. The following statistical tests were performed to determine the relationships between the variables and the answers to the research questions and subsidiary questions that were posed in Section 1.3.

- **Descriptive Analysis**: Descriptive statistics was used to describe the dependent variables (Performance), and the independent variables (Anxiety toward Statistics, Attitude toward Statistics and Mathematics Self-concept). The analysis showed that students developed a more negative attitude toward statistics during the semester, and that students gained more confidence in doing mathematics toward the end of the semester. Also, it was indicated that students had high anxiety levels at the beginning of the semester.

- The main analyses on gender difference was conducted within a multivariate analysis variance (**MANOVA**) framework, where gender and time were the independent variables and Anxiety toward Statistics, Attitude toward Statistics, Mathematics Self-concept and six anxiety sub-scales were dependent variables. Also, parametric assumptions of MANOVA were tested.

- This research made use of statistical association to indicate the relationship among the variables through **correlation, univariate** and **multivariate analyses**. Anxiety toward Statistics was found to be moderately correlated with Attitude toward Statistics. This meant that an increase in anxiety levels lead to better/worse attitude toward statistics. Mathematics Self-concept was not significantly correlated with Anxiety toward Statistics and Attitude toward Statistics. Correlations between the six anxiety sub-scales were found to be positive and significant. There was a significant univariate association between Anxiety toward Statistics, Attitude toward Statistics, Mathematics Self-concept and Performance. Anxiety and Attitude toward Statistics were found to have a significant negative relationship with performance, while Mathematics Self-concept was found to have positively significant relationship with performance. Fear of Asking for Help and Computation Self-concept were found to have a significantly negative relationship with performance but with small R^2, suggesting that there are other variables which also affect students' performance. There was a significant multivariate association between Mathematics Self-concept and performance. Mathematics Self-concept had a positively significant relationship with performance. The research also showed a significant multivariate association between Computation Self-concept and performance. Computation Self-concept negatively affected students' performance but with small R^2.

- Both regression models and path analysis were tested for multicollinearity. The primary concern with multicollinearity is that, as the degree of multicollinearity increases, the regression model estimates of the coefficients become unstable and the standard errors for the coefficients can get inflated. The presence of multicollinearity can result in the detrimental output of results with regard to regression analysis and path analysis. In order to account for multicollinearity, variables with high VIF were removed in a sensitivity-testing procedure.

- The **Path Modelling** (extension of regression modelling) results indicated that, Attitude toward Statistics had a significantly negative effect on Performance while Mathematics Self-concept had a significantly positive effect on Performance. Computation self-concept had a significantly negative effect on Performance. These results suggested that, the higher the negative attitude of students, the worse the students' performance. In addition, the results suggested that the more students are comfortable with mathematics the better the performance in statistics.

5.4 Summary of significant findings

Various statistical tests testing the relationship between attitude toward statistics, mathematics self-concept, computation self-concept and performance were significant (although not all tests were significant).

- There was a significant and negative relationship between Attitude toward Statistics and Performance. There was a significant positive correlation between Anxiety toward Statistics and Attitude toward Statistics. This suggest that both anxiety and attitude influenced each other, the higher the anxiety scores, the higher the attitude scores (see section 4.5.1).

- There was a positive and significant relationship between Mathematics Self-concept and Performance. This means that the higher the mathematics self-concept the higher the performance.

- There was significant and negative anxiety regarding Computation Self-concept. The higher the computation self-concept, the lower the performance.

- Significant and positive correlations were obtained between the six STARS anxiety sub-scales. This meant that all the sub-scales were inter-connected.

5.5 Conclusions from the Qualitative results

The second objective of the empirical investigation was to gather qualitative information on the experiences and opinions of students regarding statistics anxiety and their attitude toward statistics by means of interviews. Six students were interviewed about their experiences and opinions about the introductory statistics course.

The qualitative analysis provided supporting evidence for the results obtained in the quantitative analysis. Most students stated that they were anxious at the beginning of the semester. They stated that their anxiety affected their attitude toward statistics and that their attitude changed throughout the semester. Students voiced that there were factors which changed and influenced their attitude, anxiety and mathematics self-concept. Some students indicated that time constraint, translation of study materials, work capacity and inclusion of mathematics in the statistics module increased their level of anxiety which also influenced their attitude to be negative toward statistics. Most students with a good mathematics self-concept were confident in studying statistics. Some students stated that they experienced psychological symptoms such as racing heart, panics and sweating.

5.6 Significance of the study

There are limited studies related to statistics anxiety in Africa. This study contributes to the body of research and knowledge on statistics anxiety among first year students at higher learning institutions; it also point to various socio-cultural sources of statistics anxiety. It also states useful recommendations. Moreover, the literature revealed that more research in Republic of South Africa was necessary using both subjective and objective measures. This study has managed to investigate statistics anxiety using subjective measures (scores from an anxiety questionnaire). The findings state (and substantiate the literature) that the higher the anxiety levels of an individual student, the poorer they are likely to perform.

Additionally, the findings indicate that in the sample that was investigated for this research study, statistics anxiety was not affected by gender but by statistics experiences and mathematics background. For these reasons, this study adds to the understanding regarding statistics anxiety in the South African context.

5.7 Limitations

The current study is intended to provide evidence on association between statistics anxiety, attitude toward statistics and mathematics self-concept to students performance in an introductory statistics class. Several limitations on this empirical study were identified.

- All of the measures used in this study are self-reported and therefore possibly subject to bias. Minor variations in the structure of the questions of the self-report questionnaire (e.g question wording and order) can lead to significant discrepancies in findings. In addition, variations in mode of administration (how, what, when, and in what manner the self-report questionnaire is provided) can also be a dramatic source of study bias.

- Students who may feel under pressure to appear socially desirable may under-report their levels of statistics anxiety as well as over-report their levels of positive attitude and feeling toward statistics.

- There were three sections for participants to answer in the study. The time constraint burden on students to finish the instrument might have resulted in dishonesty.

- Another concern is the transferability of the results to other institutions that offer similar introductory courses. Because non-probability sampling methods were used instead of random sampling, the results cannot be generalised to the population.

- Finally, there may be variables that could influence the students' statistical performance that were not measured in this study. Variables such as class attendance and whether statistics was a main course or not were not taken into account.

Despite these limitations, results from the present study provide insight into the relationship between statistics anxiety, attitude toward statistics and mathematics self-concept in a statistics introductory class.

5.8 Recommendations

Bearing in mind the research findings, as well as the limitations (see section 5.7), the following recommendations are made:

- There should be a learning system to allow for anonymous questions because some students experience anxiety related to *Fear of Asking for Help* and *Fear of Statistics Teacher* (Cruise et al., 1985). For example, the Blackboard learning system could be implemented, allowing the lecturer to set up forums for students to post questions anonymously.
- Separate classes should be offered to students having little mathematics background so that they can learn at a slower pace than those comfortable with mathematics.
- The study could be repeated by selecting a random sample from all undergraduate statistics students. The results of the proposed research study could then be generalised to statistics students at all universities in South Africa.
- The universities should introduce a pre-entry program for statistics to all first year students, to introduce basic statistics concepts to them, thus lowering statistics anxiety and allowing for improved performance.
- Construct related validity should be examined by correlating sections and sub-scales on the STARS with sections and sub-scales on other instruments such as the Attitudes toward Statistics (ATS) (Wise, 1985).

- The findings should be shared on an international level at conferences and in scholarly publications. In this way the study can contribute internationally to the advancement of the scholarship of teaching and learning on the disciplinary level.

References

Ajzen, I. (1989). Attitude structure and behavior. *Attitude structure and function*, pages 241–274.

Al-Ansi, A. M., Rahardjo, K., and Prasetya, A. (2015). Analysis impact of leadership style and pay fairness on job satisfaction and organizational commitment. *Management*, 5(2):55–61.

Alexander, L. and Martray, C. R. (1989). The development of an abbreviated version of the mathematics anxiety rating scale. *Measurement and Evaluation in counseling and development*.

Ali, A. Z. and Iqbal, F. (2012). Statistics anxiety among psychology graduates: An analysis. *International Proceedings of Economics Development and Research*, 53(25):113–117.

Babbie, E. and Mouton, J. (2001). Qualitative data analysis. *The Practice of Social Research, South African Edition*.

Baharun, N. and Porter, A. (2009). Removing the angst from statistics. *Centre for Statistical and Survey Methodology*, 6(5).

Baloglu, M. (2002). Psychometric properties of the statistics anxiety rating scale. *Psychological Reports*, 90(1):315–325.

Baloglu, M. (2004). Statistics anxiety and mathematics anxiety: Some interesting differences i. *Educational Research Quarterly*, 27(3):38.

Baloglu, M. and Zelhart, P. (2003). Statistical anxiety: A detailed review of the literature. *PSYCHOLOGY AND EDUCATION-ORANGEBURG-*, 40(2):27–37.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Prentice-Hall, Inc.

Barkley, C. A. (1995). *A study of misconceptions in statistics and statistics anxiety: Affect and performance in an undergraduate math course.*

Beaglehole, R. and Bonita, R. (1993). Kjellström. basic epidemiology. *World Health Organization, Geneva.*

Bell, J. A. (2008). Statistics anxiety and business statistics: The international student. *Education*, 129(2):282.

Belsley, D. A. (1991). *Conditioning diagnostics: Collinearity and weak data in regression.* Number 519.536 B452. Wiley.

Benson, J. (1989). Structural components of statistical test anxiety in adults: An exploratory model. *The Journal of Experimental Education*, 57(3):247–261.

Benson, J. and Bandalos, D. L. (1988). A structural model of statistical test anxiety in adults.

Bernard, E. and Whitley, J. (2002). Principles of research in behavioral science.

Birenbaum, M. and Eylath, S. (1994). Who is afraid of statistics? correlates of statistics anxiety among students of educational sciences. *Educational Research*, 36(1):93–98.

Blalock Jr, H. M. (1987). Some general goals in teaching statistics. *Teaching Sociology*, pages 164–172.

Blanche, M. T., Durrheim, K., and Painter, D. (2006). *Research in practice: Applied methods for the social sciences.* Juta and Company Ltd.

Bless, C., Higson-Smith, C., and Kagee, A. (2006). *Fundamentals of social research methods: An African perspective.* Juta and Company Ltd.

Bollen, K. A. (2014). *Structural equations with latent variables.* John Wiley & Sons.

Borkovec, T. D., Robinson, E., Pruzinsky, T., and DePree, J. A. (1983). Preliminary exploration of worry: Some characteristics and processes. *Behaviour research and therapy*, 21(1):9–16.

Bowen, W. G. and Rudenstine, N. L. (1992). In pursuit of the ph. d. princeton.

Bowerman, B. L. and O'connell, R. T. (1990). *Linear statistical models: An applied approach.* Brooks/Cole.

Bradstreet, T. E. (1996). Teaching introductory statistics courses so that nonstatisticians experience statistical reasoning. *The American Statistician*, 50(1):69–78.

Brayne, C., Gill, C., Huppert, F., Barkley, C., Gehlhaar, E., Girling, D., O'Connor, D., and Paykel, E. (1995). Incidence of clinically diagnosed subtypes of dementia in an elderly population. cambridge project for later life. *The British Journal of Psychiatry*, 167(2):255–262.

Brooks, C. et al. (2008). Rats handbook to accompany introductory econometrics for finance. *Cambridge Books*.

Buck, J. L. (1987). More on superiority of women in statistics achievement: A reply to brooks. *Teaching of Psychology*, 14(1):45–46.

Burns, N. and Grove, S. K. (1993). The practice of nursing research. *Conduct, critique & utilization*, 4.

Byrd, P. (1982). *A descriptive study of mathematics anxiety: Its nature and antecedents.*

Caine, R., Centa, D., Doroff, C., Horowitz, J. H., and Wisenbaker, V. (1978). Statistics from whom? *Teaching Sociology*, pages 37–46.

Carey, G. (1998). Multivariate analysis of variance (manova): I. theory. *Retrieved May*, 14:2011.

Carmines, E. G. and Zeller, R. A. (1979). *Reliability and validity assessment*, volume 17. Sage publications.

Cesari, J. P. (1990). Thesis and dissertation support groups-a unique service for graduate-students.

Chambers, J. M., Cleveland, W. S., Kleiner, B., Tukey, P. A., et al. (1983). *Graphical methods for data analysis*, volume 5. Wadsworth Belmont, CA.

Chew, P. K. and Dillon, D. B. (2014). Statistics anxiety update refining the construct and recommendations for a new research agenda. *Perspectives on Psychological Science*, 9(2):196–208.

Clayton, K. N. (1984). An introduction to statistics. *Columbus, OH: Merrill.*

Collins, K. M. and Onwuegbuzie, A. J. (2007). I cannot read my statistics textbook: The relationship between reading ability and statistics anxiety. *The Journal of Negro Education*, pages 118–129.

Colman, A. (2001). A dictionary of psychology, projective tests.

Creswell, J. W. (2002). Educational research: Planning, conducting, and evaluating quantitative. *New Jersey: Upper Saddle River.*

Cruise, R. J., Cash, R. W., and Bolton, D. L. (1985). Development and validation of an instrument to measure statistical anxiety. *Proceedings of the American Statistical Association, Section on Statistical Education, Las Vegas, NV.*

Cruise, R. J. and Wilkins, E. M. (1980). Stars: Statistical anxiety rating scale. *Unpublished manuscript, Andrews University, Berrien Springs, MI*, 20.

De Klerk, B. (2011). *A critical appraisal of selection criteria and academic progression of first and second year medical students at the University of the Free State.* PhD thesis, University of the Free State.

de Leeuw, J. (2004). Unidimensional scaling. *Department of Statistics, UCLA*.

De Vaus, D. (2002). Surveys in social science research.

Dempster, M. and McCorry, N. K. (2009). The role of previous experience and attitudes toward statistics in statistics assessment outcomes among undergraduate psychology students. *Journal of Statistics Education*, 17(2):1–7.

DeVaney, T. A. (2010). Anxiety and attitude of graduate students in on-campus vs. online statistics courses. *Journal of Statistics Education*, 18(1):1–15.

DeVellis, R. F. (2016). *Scale development: Theory and applications*, volume 26. Sage publications.

Dew, K. H., Galassi, J. P., and Galassi, M. D. (1984). Math anxiety: Relation with situational test anxiety, performance, physiological arousal, and math avoidance behavior. *Journal of Counseling Psychology*, 31(4):580.

Diaz, R. J., Glass, C. R., Arnkoff, D. B., and Tanofsky-Kraff, M. (2001). Cognition, anxiety, and prediction of performance in 1st-year law students. *Journal of Educational Psychology*, 93(2):420.

Dillon, K. M. (1982). Statisticophobia. *Teaching of Psychology*, 9(2):117.

Druggeri, K., Dempster, M., Hanna, D., and Cleary, C. (2008). Experiences and expectations: The real reason nobody likes stats. *Psychology Teaching Review*, 14(2):75–83.

Dykeman, B. F. (2011). Statistics anxiety: Antecedents and instructional interventions. *Education*, 132(2):441.

Earp, M. S. (2007). *Development and validation of the statistics anxiety measure*. PhD thesis, Citeseer.

Eduljee, N. B. and LeBourdais, P. (2015). Gender differences in statistics anxiety with undergraduate college students. *The International Journal of Indian Psychology*, 2(3).

Erdogan, F. and Sengul, S. (2014). A study on the elementary school students mathematics self concept. *Procedia-Social and Behavioral Sciences*, 152:596–601.

Evans, B. (2007). Student attitudes, conceptions, and achievement in introductory undergraduate college statistics. *The Mathematics Educator*, 17(2).

Everitt, B. S. and Dunn, G. (2001). *Applied multivariate data analysis*, volume 2. Wiley Online Library.

Ezekiel, M. and Fox, K. A. (1959). Methods of correlation and regression analysis: linear and curvilinear.

Fennema, E. and Sherman, J. A. (1976). Fennema-sherman mathematics attitudes scales: Instruments designed to measure attitudes toward the learning of mathematics by females and males. *Journal for Research in Mathematics Education*, 7(5):324–326.

Finney, S. J. and Schraw, G. (2003). Self-efficacy beliefs in college statistics courses. *Contemporary Educational Psychology*, 28(2):161–186.

Firmin, M. and Proemmel, E. (2011). Towards remediating undergraduate students statisticophobia. *College Teaching Methods and Styles Journal (CTMS)*, 4(4):17–20.

Fitzgerald, S. M., Jurs, S. J., and Hudson, L. M. (1996). A model predicting statistics achievement among graduate students. *College Student Journal*.

Fraenkel, J. and Wallen, N. (2008). Introduction to qualitative research. *How to Design and Evaluate Research in Education, 7th ed. Boston, MA: McGraw-Hill International Edition*.

French, A., Macedo, M., Poulsen, J., Waterson, T., and Yu, A. (2008). Multivariate analysis of variance (manova). *San Francisco State University*.

Freund, R. and Wilson, W. (1998). Problems with the model.

Gadzella, B. M. and Baloglu, M. (2001). Confirmatory factor analysis and internal consistency of the student-life stress inventory. *Journal of Instructional Psychology*, 28(2):84.

Gal, I. and Ginsburg, L. (1994). The role of beliefs and attitudes in learning statistics: Towards an assessment framework. *Journal of Statistics Education*, 2(2):1–15.

Gal, I., Ginsburg, L., and Schau, C. (1997). Monitoring attitudes and beliefs in statistics education. *The assessment challenge in statistics education*, pages 37–51.

Garson, G. D. (2008). Path analysis. *from Statnotes: Topics in Multivariate Analysis. Retrieved*, 9(05):2009.

Graziano, A. and Raulin, M. (1989). Hypothesis testing, validity, and threats to validity. *Research Methods: A Process of Inquiry*, pages 153–177.

Gujarati, D. N. (2004). Economics basic econometrics.

Hanna, D. and Dempster, M. (2009). The effect of statistics anxiety on studentsâĂŹ predicted and actual test scores. *The Irish Journal of Psychology*, 30(3-4):201–209.

Harvill, L. M. (1991). Standard error of measurement. *Educational Measurement: issues and practice*, 10(2):33–41.

Hawkey, P. L. (1995). *Mathematics anxiety as a variable in the constructivist approach to the teaching of secondary school mathematics*. PhD thesis.

Hembree, R. (1988). Correlates, causes, effects, and treatment of test anxiety. *Review of educational research*, 58(1):47–77.

Henning, E., Van Rensburg, W., and Smit, B. (2004). *Finding your way in qualitative research*. Van Schaik Pretoria.

Hochberg, Y. (1988). A sharper bonferroni procedure for multiple tests of significance. *Biometrika*, 75(4):800–802.

Ivankova, N., Creswell, J., and Plano Clark, V. (2007). Foundations and approaches to mixed methods research. *First steps in research. Pretoria: Van Schaik*, pages 253–282.

Johnson, N. L. and Leone, F. C. (1964). Statistical and experimental design, vol. 2.

Katzenellenbogen, J. M., Joubert, G., and Karim, S. A. (1997). *Epidemiology: a manual for South Africa*. Oxford University Press.

Keeley, J., Zayac, R., and Correia, C. (2008). Curvilinear relationships between statistics anxiety and performance among undergraduate students: Evidence for optimal anxiety. *Statistics Education Research Journal*, 7(1):4–15.

Kerlinger, F. (1986). Foundations of behavioral research (holt, rinehart and winston, new york, ny).

Koh, D. and Zawi, M. K. (2014). Statistics anxiety among postgraduate students. *International Education Studies*, 7(13):166.

Kolmogorov, A. N. (1933). Foundations of probability.

Kutner, M., Nachtsheim, C., Neter, J., and Li, W. (2005). Pages 384-420 in: Applied linear statistical models.

Lacasse, C. and Chiocchio, F. (2005). Anxiety towards statistics: Further developments and issues. In *66th Conference of the Canadian Psychological Association. Montreal, Quebec, Canadal*, volume 20052004, page 1.

Lalonde, R. N. and Gardner, R. C. (1993). Statistics as a second language? a model for predicting performance in psychology students. *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement*, 25(1):108.

Lance, C. E., Butts, M. M., and Michels, L. C. (2006). The sources of four commonly reported cutoff criteria what did they really say? *Organizational research methods*, 9(2):202–220.

Lazaridis, I. and Tryfonidis, D. (2006). Relationship between working capital management and profitability of listed companies in the athens stock exchange.

Lekalakala, M. J. (2007). *Teachers perceptions about lesson planning to include an environmental education focus*. PhD thesis, University of Johannesburg.

Litwin, M. S. and Fink, A. (1995). *How to measure survey reliability and validity*, volume 7. Sage.

Liu, S., Onwuegbuzie, A., and Meng, L. (2011). Examination of the score reliability and validity of the statistics anxiety rating scale in a chinese population: Comparisons of statistics anxiety between chinese college students and their western counterparts. *Journal of Educational Enquiry*, 11(1):29–42.

Lundgren, T. D. and Fawcett, R. (1980). Statistics from statisticians: Comment on caine, centa, doroff, horowitz, and wisenbaker, ts, october 1978. *Teaching Sociology*, pages 191–201.

Ma, X. and Kishor, N. (1997). Assessing the relationship between attitude toward mathematics and achievement in mathematics: A meta-analysis. *Journal for research in mathematics education*, pages 26–47.

Macher, D., Paechter, M., Papousek, I., and Ruggeri, K. (2012). Statistics anxiety, trait anxiety, learning behavior, and academic performance. *European journal of psychology of education*, 27(4):483–498.

Malhotra, N. K. and Malhotra, N. K. (2012). *Basic marketing research: Integration of social media*. Pearson Boston.

Malik, S. (2015). Undergraduates' statistics anxiety: A phenomenological study. *The Qualitative Report*, 20(2):120.

Marsh, H. W. and O'Neill, R. (1984). Self description questionnaire iii: the construct validity of multidimensional self-concept ratings by late adolescents. *Journal of Educational Measurement*, 21(2):153–174.

McMillan, J. S. (2001). Research in education: Evidence-based inquiry. *Research in Education. A Conceptual Introduction (5th Ed), New York, Addison Wesly Longman.*

Mills, J. D. (2004). Students'attitudes toward statistics: Implications for the future. *College Student Journal*, 38(3):349.

Mji, A. (2009). Differences in university students'attitudes and anxiety about statistics 1. *Psychological reports*, 104(3):737–744.

Mji, A. and Onwuegbuzie, A. J. (2004). Evidence of score reliability and validity of the statistical anxiety rating scale among technikon students in south africa. *Measurement and Evaluation in Counseling and Development*, 36(4):238.

Montgomery, D. C., Peck, E. A., and Vining, G. G. (2015). *Introduction to linear regression analysis*. John Wiley & Sons.

Morrison, D. F. (1998). *Multivariate analysis, overview*. Wiley Online Library.

Musch, J. and Broder, A. (1999). Test anxiety versus academic skills: A comparison of two alternative models for predicting performance in a statistics exam. *British Journal of Educational Psychology*, 69(1):105–116.

Myers, M. D. et al. (1997). Qualitative research in information systems. *Management Information Systems Quarterly*, 21(2):241–242.

Nasser, F. M. (2004). Structural model of the effects of cognitive and affective factors on the achievement of arabic-speaking pre-service teachers in introductory statistics. *Journal of Statistics Education*, 12(1).

Neill, J. (2007). Qualitative versus quantitative research: Key points in a classic debate. *Qualitative Versus Quantitative Research*.

Nunnally, J. (1978). Psychometric methods.

Nunnally, J. C. and Bernstein, I. (1994). The assessment of reliability. *Psychometric theory*, 3(1):248–292.

Onwuegbuzie, A. J. (1993). *The interaction of statistics test anxiety and examination condition in statistics achievement of post-baccalaureate non-statistics majors.*

Onwuegbuzie, A. J. (1998). The dimensions of statistics anxiety: A comparison of prevalence rates among mid-southern university students. *Louisiana Educational Research Journal*, 23(2):23–40.

Onwuegbuzie, A. J. (1999). Statistics anxiety among african american graduate students: An affective filter? *Journal of Black Psychology*, 25(2):189–209.

Onwuegbuzie, A. J. (2000). Expanding the framework of internal and external validity in quantitative research.

Onwuegbuzie, A. J. (2004). Academic procrastination and statistics anxiety. *Assessment & Evaluation in Higher Education*, 29(1):3–19.

Onwuegbuzie, A. J., Bailey, P., and Daley, C. E. (1999). Factors associated with foreign language anxiety. *Applied Psycholinguistics*, 20(02):217–239.

Onwuegbuzie, A. J., Da Ros, D., and Ryan, J. M. (1997). The components of statistics anxiety: A phenomenological study. *Focus on Learning Problems in Mathematics*, 19(4):11–35.

Onwuegbuzie, A. J. and Seaman, M. A. (1995). The effect of time constraints and statistics test anxiety on test performance in a statistics course. *The Journal of experimental education*, 63(2):115–124.

Onwuegbuzie, A. J. and Wilson, V. A. (2003). Statistics anxiety: Nature, etiology, antecedents, effects, and treatments–a comprehensive review of the literature. *Teaching in Higher Education*, 8(2):195–209.

O'Rourke, N. and Hatcher, L. (2013). *A step-by-step approach to using SAS for factor analysis and structural equation modeling.* Sas Institute.

Pagano, M., Gauvreau, K., and Pagano, M. (2000). *Principles of biostatistics*, volume 2. Duxbury Pacific Grove, CA.

Pan, W. and Tang, M. (2005). Students' perceptions on factors of statistics anxiety and instructional strategies. *Journal of Instructional Psychology*, 32(3):205.

Papanastasiou, E. C. and Zembylas, M. (2008). Anxiety in undergraduate research methods courses: Its nature and implications. *International Journal of Research & Method in Education*, 31(2):155–167.

Pearson, K. (1895). X. contributions to the mathematical theory of evolution.âĂŤii. skew variation in homogeneous material. *Phil. Trans. R. Soc. Lond. A*, 186:343–414.

Perepiczka, M., Chandler, N., and Becerra, M. (2011). Relationship between graduate students statistics self-efficacy, statistics anxiety, attitude toward statistics, and social support. *The Professional Counselor: Research and Practice*, 1(2):99–108.

Pretorius, T. B. and Norman, A. (1992). Psychometric data on the statistics anxiety scale for a sample of south african students. *Educational and Psychological Measurement*, 52(4):933–937.

Punch, K. (2003). *Survey research: The basics*. Sage.

Quinn, A. (2006). Reducingsocialworkstudents' statisticsanxiety. *Academic Exchange Quarterly*, 10(2).

Rencher, A. C. (2003). *Methods of multivariate analysis*, volume 492. John Wiley & Sons.

Richardson, F. C. and Suinn, R. M. (1972). The mathematics anxiety rating scale: psychometric data. *Journal of counseling Psychology*, 19(6):551.

Richardson, F. C. and Woolfolk, R. L. (1980). Mathematics anxiety. *Test anxiety: Theory, research, and applications*, pages 271–288.

Roberts, D. M. and Bilderback, E. W. (1980). Reliability and validity of a statistics attitude survey. *Educational and Psychological Measurement*, 40(1):235–238.

Rosenthal, R. and Rosnow, R. L. (1991). *Essentials of behavioral research: Methods and data analysis*. McGraw-Hill Humanities Social.

Rucci, P., Rossi, A., Mauri, M., Maina, G., Pieraccini, F., Pallant, S., Camilleri, V., Montagnani, M. S., Endicott, J., and Equip, P. I. G. (2007). Validity and reliability of the quality of life, enjoyment and satisfaction questionnaire, short form. *Epidemiology and Psychiatric Sciences*, 16(1):82–87.

Sarason, I. G. (1980). *Test anxiety: Theory, research, and applications*. Lawrence Erlbaum Assoc Inc.

Satake, E. and Amato, P. P. (1995). Mathematics anxiety and achievement among japanese elementary school students. *Educational and Psychological Measurement*, 55(6):1000–1007.

Schacht, S. and Stewart, B. J. (1990). What's funny about statistics? a technique for reducing student anxiety. *Teaching Sociology*, 18(1):52–56.

Schau, C. (2003). Students attitudes: The other important outcome in statistics education. In *Proceedings of the joint statistical meetings*, pages 3673–3681.

Shah Abd Hamid, H. and Sulaiman, M. K. (2014). Statistics anxiety and achievement in a statistics course among psychology students. *International Journal of Behavioral Science (IJBS)*, 9(1).

Shapiro, S. S. and Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, 52(3/4):591–611.

Sherard, W. H. (1981). Math anxiety in the classroom. *The Clearing House*, 55(3):106–110.

Shultz, K. S. and Koshino, H. (1998). Evidence of reliability and validity for wise's attitude toward statistics scale. *Psychological Reports*, 82(1):27–31.

Smirnov, N. (1948). Table for estimating the goodness of fit of empirical distributions. *The annals of mathematical statistics*, 19(2):279–281.

Stevens, J. P. (2012). *Applied multivariate statistics for the social sciences*. Routledge.

Stevens, M. (2013). Ethical issues in qualitative research. *King's College London*.

Sutarso, T. (1992). Some variables in relation to students' anxiety in learning statistics.

Tavakol, M. and Dennick, R. (2011). Making sense of cronbach's alpha. *International journal of medical education*, 2:53.

Vahedi, S., Farrokhi, F., and Bevrani, H. (2011). A confirmatory factor analysis of the structure of statistics anxiety measure: An examination of four alternative models. *Iranian journal of psychiatry*, 6(3):92.

Vigil-Colet, A., Lorenzo-Seva, U., and Condon, L. (2008). Development and validation of the statistical anxiety scale. *Psicothema*, 20(1):174–180.

Viljoen, M. (2007). *Introduction to quantitative research methods*. Bloemfontein: University of the Free State.

Vos, A., Strydom, H., Fouche, C., and Delport, C. (2005). Research at grass roots: For the social sciences and human service professions. *Pretoria: Van Schaik Publishers*.

Walsh, J. J. and Ugumba-Agwunobi, G. (2002). Individual differences in statistics anxiety: the roles of perfectionism, procrastination and trait anxiety. *Personality and Individual Differences*, 33(2):239–251.

Watson, G. S. (1964). Smooth regression analysis. *Sankhyā: The Indian Journal of Statistics, Series A*, pages 359–372.

Webb, R. J. (1972). *A study of the effects of anxiety and attitudes upon achievement in doctoral educational statistics courses*. PhD thesis, ProQuest Information & Learning.

Welman, C., Kruger, F., and Mitchell, B. (2005). *Research methodology.* Oxford University Press.

Wentzel, K. R. (1998). Social relationships and motivation in middle school: The role of parents, teachers, and peers. *Journal of educational psychology*, 90(2):202.

Westfall, P. H. and Young, S. S. (1993). *Resampling-based multiple testing: Examples and methods for p-value adjustment*, volume 279. John Wiley & Sons.

Wheeler, D. and Tiefelsdorf, M. (2005). Multicollinearity and correlation among local regression coefficients in geographically weighted regression. *Journal of Geographical Systems*, 7(2):161–187.

Williams, A. (2014). An exploration of preference for numerical information in relation to math self-concept and statistics anxiety in a graduate statistics course. *Journal of Statistics Education*, 22(1):1–16.

Williams, A. S. (2010). Statistics anxiety and instructor immediacy. *Journal of Statistics Education*, 18(2):1–18.

Wise, S. L. (1985). The development and validation of a scale measuring attitudes toward statistics. *Educational and Psychological Measurement*, 45(2):401–405.

Wright, S. (1920). The relative importance of heredity and environment in determining the piebald pattern of guinea-pigs. *Proceedings of the National Academy of Sciences*, 6(6):320–332.

Wright, S. (1921). Correlation and causation. *Journal of agricultural research*, 20(7):557–585.

Wright, S. (1923). The theory of path coefficients a reply to niles's criticism. *Genetics*, 8(3):239–255.

Zanakis, S. H. and Valenzi, E. R. (1997). Student anxiety and attitudes in business statistics. *Journal of Education for Business*, 73(1):10–16.

Zbornik, J. (2001). Make sure your math anxiety diagnosis, remediation add up. *Todays School Psychologist*, 5(5):3–8.

Zeidner, M. (1991). Statistics and mathematics anxiety in social science students: Some interesting parallels. *British Journal of Educational Psychology*, 61(3):319–328.

Zerbolio Jr, D. J. (1989). A'bag of tricks' for teaching about sampling distributions. *Teaching of Psychology*, 16(4):207–209.

Appendices

Appendix A

Questionnaires

UNIVERSITY OF THE FREE STATE
DEPARTMENT OF MATHEMATICAL STATISTICS AND ACTUARIAL SCIENCE

May 2016 | **F** | **M** | **Last 4 digits of std number** |

Dear Student

Thank you for giving your attention to this questionnaire. The time needed to complete the questionnaire is about 20 minutes. The purpose of the questions is to explore students' anxiety and feeling towards statistics.

Information obtained will be strictly used for the purpose of research. By completing this questionnaire, you are giving the researcher consent to use the information for research purposes only. Responses will be confidential; that is, your privacy will be protected to the maximum extent allowable by law.

Participation is voluntary. Completing or failing to complete this questionnaire has absolutely no bearing on your grade.

On a scale of 1 – 5, indicate the extent to which you feel anxious about the following statements.	No anxiety	Partially anxiety	Neutral	Anxiety	Very much anxiety
A. *Anxiety*					
1. Studying for an examination in a statistics course.	1	2	3	4	5
2. Going to ask my statistics teacher for individual help with material I am having difficulty understanding.	1	2	3	4	5
3. Doing the homework for a statistics course.	1	2	3	4	5
4. Doing the final examination in a statistics course.	1	2	3	4	5
5. Working into the classroom to take a statistics test.	1	2	3	4	5
6. Interpreting the meaning of a probability value once I have found it.	1	2	3	4	5
7. Finding that another student in class got a different answer than you did to a statistical problem.	1	2	3	4	5
8. Figuring out whether to reject or retain the null hypothesis.	1	2	3	4	5
9. Waking up in the morning on the day of a statistics test.	1	2	3	4	5
10. Trying to understand the odds in a lottery.	1	2	3	4	5

11. Enrolling a statistics course.	1	2	3	4	5
B. ***Feeling towards statistics***	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. Since I am by nature a subjective person the objectivity of statistics is inappropriate for me.	1	2	3	4	5
2. I haven't had mathematics for a long time. I know I'll have problems getting through statistics.	1	2	3	4	5
3. I wonder why I have to do all these things in statistics when in actual life I'll never use them.	1	2	3	4	5
4. Statistics is worthless to me since it's empirical and my area of specialization is philosophical.	1	2	3	4	5
5. Statistics takes more time than it's worth.	1	2	3	4	5
6. I feel statistics is waste.	1	2	3	4	5
7. Statistics teachers are so abstract they seem inhuman.	1	2	3	4	5
8. I can't even understand seventh- and eighth-grade mathematics; how can I possibly understand statistics.	1	2	3	4	5
9. Most statistics teachers are inhuman.	1	2	3	4	5
10. I lived this long without knowing statistics. Why should I learn it now?	1	2	3	4	5
11. Since I've never enjoyed mathematics. I don't see how I can enjoy statistics.	1	2	3	4	5
12. I don't want to learn to like statistics.	1	2	3	4	5
13. Statistics is for people who have a natural learning toward mathematics.	1	2	3	4	5
14. Statistics is a grind a pain I could do without.	1	2	3	4	5
15. I could enjoy statistics if it weren't so mathematical.	1	2	3	4	5

16. I wish the statistics requirement would be removed from my academic program.	1	2	3	4	5
17. I don't understand why someone in my field needs Statistics.	1	2	3	4	5
18. I don't see why I have to clutter up my head with statistics. It has no significance to my life work.	1	2	3	4	5
19. Statistics teachers talk a different language.	1	2	3	4	5
20. I can't tell you why but I just don't like statistics.	1	2	3	4	5
21. Statistics teachers talk so fast you cannot logically follow them.	1	2	3	4	5
22. Statistics figures are not fit for human consumption.	1	2	3	4	5
23. Statistics isn't really bad. It's just too mathematical.	1	2	3	4	5
24. I am never going to use statistics so why should I have to take it?	1	2	3	4	5
25. I'm too slow in my thinking to get through statistics.	1	2	3	4	5

C. ***Mathematics Self-Concept***	Never	Some times	Most of the time	Always
1. I find many mathematical problems interesting and challenging.	1	2	3	4
2. I have hesitated to take courses that involve mathematics.	1	2	3	4
3. I have generally done better in mathematics courses than other courses.	1	2	3	4
4. Mathematics makes me feel inadequate.	1	2	3	4
5. I am quite good in mathematics.	1	2	3	4
6. I have trouble understanding anything that is based upon mathematics.	1	2	3	4

7. I have done well in mathematics classes.	1	2	3	4
8. I did not do well in tests that require mathematics reasoning.	1	2	3	4
9. At school, my friends came to me for help in mathematics.	1	2	3	4
10. I have been very excited about mathematics	1	2	3	4

Appendix B

Interview Questions

Research Interview Questions

1. Do you like statistics? Why/why not?

2. Was it difficult for you to learn statistics?

   Were there specific topics that was difficult to learn?

3. What do you believe is statistics anxiety?

4. What was your attitude toward and anxiety about statistics in the beginning of the year? Did it change during the course of the semester?

   Was it negative or positive?

   Did your attitude change during the semester?

5. Do you think that the fact that you were anxious had any effect on your performance in statistics?

   Do you think that it had an effect on your test and exam marks?

6. Did you experience any physiological symptoms such as a panic attack, heart racing or feeling scared when you do statistics or write the tests and exams?

7. What are the factors that increased your levels of statistics anxiety?

   Was it the interpretation of the answers?
   Was it the mathematical calculations?
   Was it about writing the tests and exams?
   Had you any fear for asking for help?

8. What are the factors that decreased your levels of statistics anxiety?

   Did the tutorials help to decrease anxiety?

   Did the assistance of the tutors help to decrease anxiety?

9. What do you think about the statistics teacher? Did he/she make you feel more anxious? Why?

10. Were you comfortable in doing the mathematics included in the stats module?

Do you like mathematics or are you afraid of doing mathematics?

11. Did you ever feel inadequate to do statistics?

12. Did you ever feel like giving up statistics or rather do it at a later stage?

13. Do you feel statistics is a waste of time or does it make sense to you that you will use and apply it some or other time in the future?

14. If you had a choice, would you do a statistics module or rather another non-mathematical module in its place?