Structural equation modeling applied to proposed statistics attitudes-outcomes model: a case of North-West University statistics students

Dissertation Submitted in fulfilment of the requirements for the Degree of Master of Commerce in Statistics in the Faculty of Commerce and Administration, School of Economics and Decision Sciences at North-West University (Mafikeng Campus)

by

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Declaration

I, Andrew Bokang Ncube, hereby declare that this dissertation entitled "*Structural Equation Modeling Applied to Proposed Statistics Attitudes-Outcomes Model: A case of North-West University Statistics Students"* is my own work, and that all the reviewed sources I have used herein have been indicated or acknowledged in the reference list.

A.B. NCUBE	**DATE**
PROF N.D. MOROKE	**DATE**

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Abstract

The purpose of this study was to investigate the structural relationships among students' self-reported statistics anxiety, their attitudes toward statistics, and statistics outcomes by testing the proposed statistics attitudes-outcomes model. This study utilized a survey research design, SEM and PLS methodologies. The participants of the current study consisted of 583 first-year undergraduate students enrolled in statistics courses in a university in South Africa. There were 49 variables altogether. The participants were from different programmes within the Commerce Faculty. The modified versions of the Survey of Attitudes toward Statistics-36 and MPSP were used to collect data. The modified SATS-36 and MPSP served to confirm the factor structure of components of statistics attitudes including self-efficacy, anxiety and statistics outcome.

Confirmatory factor analysis results revealed that five of the nine factors were unreliable and thus invalid, using Cronbach's alpha measure of item consistency. The best model, after modification had higher model fit indices. This model used 448 observations; and the chi-square (< 0.0001) was significant implying bad fit perhaps due to many variables and large sample size used. The root mean square error of approximation (= 0.0491) is less than the cut-off criterion on 0.5 implying good fit. The probability of close fit (=0.6648) showed an improvement after variable and case deletion. The comparative fit index (=0.8792) was steadily on the increase due to the deletion of variables and cases, as well. The overall model had acceptable fit. With indices very close to the 0.90 cut off criterion. In contrast, exploratory factor analysis revealed that all but two of the constructs, had good to excellent reliability and eight variables been consequently deleted due to them being below the cut-off criterion. All other indicators had a significant loading into a construct.

All indicators of the final factor structure were found to be significantly loading into their factors after performing EFA. Structural equation modeling was used to test the hypothesised structural equation model. Partial least squares analysis reliability results are consistent with those of structural equation modeling, with only two constructs in both valid. The contradictory chi-square results and increasing fit indices suggests that the number of cases and variables has an impact on the overall fit of the model.

Keywords: Attitudes, Self-Efficacy, Statistics outcomes, Structural equation modeling, Partial Least Square.

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Chapter 1

Study orientation

1.1 Background of study

Students’ achievement in statistics depends heavily on how they learn, understand and apply the course content in their careers of choice. More important is how they perceive the course, the effort they put in, and their ability to deal with its cognitive demands. Research on undergraduate students’ perceptions and attitudes has mainly focused on constructs related to the factor structure, its reliability and validity. More focus has been on anxiety traits, mathematical competence, and gender differences. Very few of the research projects have attempted to uncover the causal relationships and covariances among measured and latent variables and how development of a positive outlook on statistics can help generate interest, relevance, motivation, effort, and the worth of the course. There is growing evidence that points to the positive effect of perceptions on positive attitudes with achievement in this course.

Students registered for commerce, administration, and some natural sciences disciplines are expected to be equipped with the necessary statistical skills in their field of choice. Expectations are that they should to be motivated to use statistics after completion of their degree programme. The contrary is true, as demonstrated by literature about the prevailing situation of statistics education (Garfield & Ben-Zvi, 2007). Statistics has proved to have a negative reputation among students. Studies suggest that statistics courses, in order to motivate students to learn statistics, need to be revised according (Carnell, 2008; Dempster & McCorry, 2009; Wiberg, 2009). Positive perceptions about statistics are of prime importance and need to be stimulated and maintained throughout a student’s academic career. Their degeneration to negative perceptions escalates to negative attitudes which inhibit any learning of statistics, as well as apprehension and application of the course content.

Large bodies of research have focused on these individual constructs’ relationship to statistics achievement rather than their interactive and mediating effect on it. It is therefore imperative to use scientific methods in studying the interactive effect of these latent variables. This may help in preventing a possible snowballing of positive perception into adverse attitudes towards students’ statistics achievement. Structural equation modeling (SEM) is such a technique. This method is capable of calculating and analysing, simultaneously, the underlying complex factor structure of observed variables (structural model), their covariances and their causal links that other multivariate techniques, such as multiple regression, multiple analyses of covariance, as well as principal component analysis, could not deal with.

The role of structural equation modeling is to simultaneously identify these relationships from a very complex structure model without being restricted by multivariate assumptions that would generally apply for certain multivariate techniques. These may range from possible aptitude checks prior to students' registration, continuous remedial mathematics skills classes, and development of students' interest, worth or value, and appreciation of statistics by giving immediate feedback and have them provide solutions to real-life problems statistically in groups and give feedback as suggested by numerous researchers. Literature shows that few studies have attempted to look into the structural relationships of variables, none which have established mediation or moderation relationships. Most of the studies have focused primarily on relationships between attitudes and achievement but have not investigated the underlying complex structural relationships (Dempster & McCorry, 2009).

None of these studies also investigated possible curriculum reconstruction to allow for statistics information retention and further enrolment in advanced statistics courses, especially in research techniques. A poor performance in statistics is often preceded by its negative perception as highlighted by Galli, Chiesi and Primi (2010). This study uses structural equation modeling to determine the plausible underlying perceptions and attitudes constructs of statistics students at the Mafikeng Campus of the North-West University. The study also analyses the possibility of causal links between manifest variables and constructs, and amongst constructs.

The remainder of this chapter is arranged as follows: section 2 deals with the *study problem statement* and section 3 contain the postulated *hypotheses and research questions of the study*. In section 4, the *research methodology* is outlined, with section 5 focusing on the *significance of the study*. Section 6 discusses *ethical considerations*, section 7, looks into the *chapter summary*. Finally, the study organisation appears in Section 8.

1.2 Problem statement

Students' misperceptions and negative attitudes may to a large extent hinder their learning, understanding, and application of statistics. Students' attitudes have been found to be intermediary between past performance and future achievement. This speaks to the retention and recruitment of students to enrol further in advanced statistics modules, research methods or change to a statistics degree programme completely. Non-attendance of statistics lectures due to non-resilience and weak self-conception is due to the students' lack of motivation and interest. Students fail to meet the cognitive demands of statistics' mathematical demands; though not misguided, may progress into students' negative attitude towards statistics. This speaks to the interest, cognitive ability, effort made by students to achieve success in the course.

In recent research, factor structure and correlations within structure models have been studied, leaving room for the study to identify covarying variables and constructs. It is for these reasons that an interaction between attitudinal affect constructs: interest, effort, cognitive competence, value or worth, enjoyment, difficulty, anxiety and perception constructs: statistics proficiency, statistics anxiety, self-perception, mathematics proficiency, and relevance are viewed as concomitants of statistics achievement. Their interaction is of interest and should be explored, and remedial intervention strategies employed at the beginning of every academic year or consistently and concurrently throughout the semesters.

SEM has the capability to do both single-level and multi-level analysis simultaneously which other first-generation models and second generation models failed to do. It can perform analysis of comparisons of multi-groups, multiple regression, multivariate analysis of covariance, combined exploratory and confirmatory factor analysis, calculate the prediction model and the associated power analysis, and do path model analysis. Thus, SEM in this study helps to remedy deficiencies of past researches by looking at the significance of moderating, mediating, causal relationships, and possible confounding factors that may arise from the model. SEM simultaneously determines parsimony and spuriousness of the final prediction model.

1.3 Aims and objectives

The aim of the study is to investigate the structural relationships among resultant latent constructs from the analysis. The primary objective of the study is to determine the effect of students' perceptions and attitudes on their statistics achievement or statistics outcome, attitudinal relationships. Furthermore, the study looks at how students' attitudes impact on their self-efficacy. Finally, this study makes an attempt to explore confirmatory and remedial properties of partial least squares (PLS) methodology to SEM limitations.

1.4 Research questions and hypotheses of study

The study attempts to respond to the following research questions:

- **Research Question 1:**

Is there a relationship between the perceptual and attitudinal constructs?

- **Research Question 2:**

Is there a relationship between students' attitudes and their self-efficacy?

- **Research Question 3:**

Can Partial Least Squares analysis be used as a remedial tool to cure Structural Equation Modeling deficiencies?

- **Research Question 4:**

Can Partial Least Squares analysis be used as a confirmatory tool?

- **Research Question 5:**

Does Statistics Anxiety have a negative effect on a students' Statistics Outcome

Study hypotheses:

The Affect factor gauges the students' positive or negative feelings towards learning statistics (Schau, 2003a), and it is a construct (an endogenous variable) in this study that can be predicted by Cognitive Competence. Emmioglu (2011) and Nolan *et al.* (2012) stated that there is a strong, statistically significant and positive correlation between the variables of Affect and Cognitive Competence. Therefore, the first hypothesis tested is:

H_1: There is positive relationship between Affect and Cognitive Competence.

Cognitive Competence is a measure of attitudes of students about their intellectual knowledge and skills towards learning statistics (Schau, 2003a). The students' cognitive ability is construct (an endogenous variable) in this study which can be predicted by Difficulty. Thus, the second hypothesis to be tested is:

H_2: There is positive relationship between Difficulty and Cognitive Competence.

Value is used to measure the students' attitudes regarding the usefulness, relevance and worth of statistics in personal and professional life (Schau, 2003a). The Value construct (is an endogenous variable) in this study since it is proposed to be predicted by Interest. Thus, the third hypothesis to be tested is:

H_3: Interest is a positive predictor of Value.

Difficulty is used to measure the students' attitudes on the difficulty of statistics as a subject (Schau, 2003a). Interest is a measure of the students' level of individual interest about the statistics subject (Schau & Emmioglu 2011). Interest construct is (an endogenous variable) that could be predicted by Affect, Cognitive Competence, and Difficulty variables. Vanhoof *et al.* (2011) have proven that correlation between Affect, Cognitive Competence, Difficulty, and Interest are high while others have proposed that the relationship between the variables of Interest and Affect, Cognitive Competence and Difficulty are strong, significant and positively correlated (Emmioglu, 2011).

Emanating from these findings, the following hypotheses are tested:

H_4: There is positive relationship between Affect and Interest.

H_5: There is positive relationship between Cognitive Competence and Interest.

H_6: There is positive relationship between Difficulty and Interest.

Effort measures the students' amount of time spent to learn statistics (Schau & Emmioglu 2011). Effort construct (is an endogenous variable) is proposed to be predicted by Interest. The relationship between the Effort and Interest is found to be moderate, statistically significant and positively correlated (Emmioglu 2011). It has been shown that correlations between Effort and Interest are statistically significant and positively correlated (Tempelaar *et al.* 2007). Thus, this leads to the following hypotheses:

H_7: There is a positive relationship between Interest and Effort.

The last construct is Statistics Anxiety which measures students' feelings of anxiety when encountering the statistics subject in any form (Onwuegbuzie *et al.*, 1997) as cited in Onwuegbuzie & Wilson (2003). A causal relationship between statistics anxiety and course achievement has been reported (Onwuegbuzie & Seaman, 1995). Literature has also investigated the relationship between statistics anxiety and achievement expectation, perfectionism, procrastination, trait anxiety, and state anxiety (Onwuegbuzie & Wilson, 2003; Walsh & Ugumba-Agwunobi, 2002). Thus a relationship with other constructs is of interest, and the following hypotheses are tested as a result:

H_8: There is a relationship between Statistics Anxiety and Statistics Outcomes.

H_9: There is a relationship between Statistics Anxiety and Effort.

H_{10}: There is a relationship between Statistics Anxiety and Affect.

H_{11}: There is a relationship between Statistics Anxiety and Difficulty.

H_{12}: There is a relationship between Statistics Anxiety and Interest.

Self-concept includes both a cognitive component and an affective component, whereas self-efficacy heavily focuses on a cognitive component. The stronger relationship between current statistics self-efficacy and the performance measures is consistent with Bandura's (1996) claim as cited in Finney & Shraw (2003). Research indicates that the closer the level of specificity of self-efficacy and self-concept, the stronger the relationship between the two constructs (Choi, 2005). The hypotheses above are represented in a structural model in Figure 1.1.

The following hypotheses are resultant:

H_{13}: There is a relationship between Difficulty and Self-efficacy.

H_{14}: There is a relationship between Effort and Self-efficacy.

H_{15}: There is relationship between Self-efficacy and Interest.

H_{16}: There is a relationship between Self-efficacy and Value.

Other proposed hypotheses:

It is the researcher's belief that students that attach value to the statistics subject spend more time doing and finishing statistics task. Furthermore, a student with a higher Cognitive Competence the more energy is expended in completing statistics task. Hence the following hypotheses are the resultant:

H17: Value has a positive relationship with Effort.

H18: Cognitive Competence has a positive relationship with Effort.

The researcher further believes that students with higher cognitive competence, statistics self-efficacy, attaches value, and puts more effort to statistics subject may achieve higher grades in the subject. The following hypotheses emanate.

H19: There is significant and positive relationship between Self-Efficacy and Statistics Outcomes.

H20: Value is a predictor of Statistics Outcomes.

H21: Effort is a positive predictor of Statistics Outcomes.

H22: Cognitive Competence has positive relationship with Statistics Outcomes.

Lastly, it is the researchers firm believe that students' statistics anxiety impacts their cognitive competence negatively. The following hypothesis is the resultant:

H23: There is positive relationship between Statistics Anxiety and Cognitive Competence.

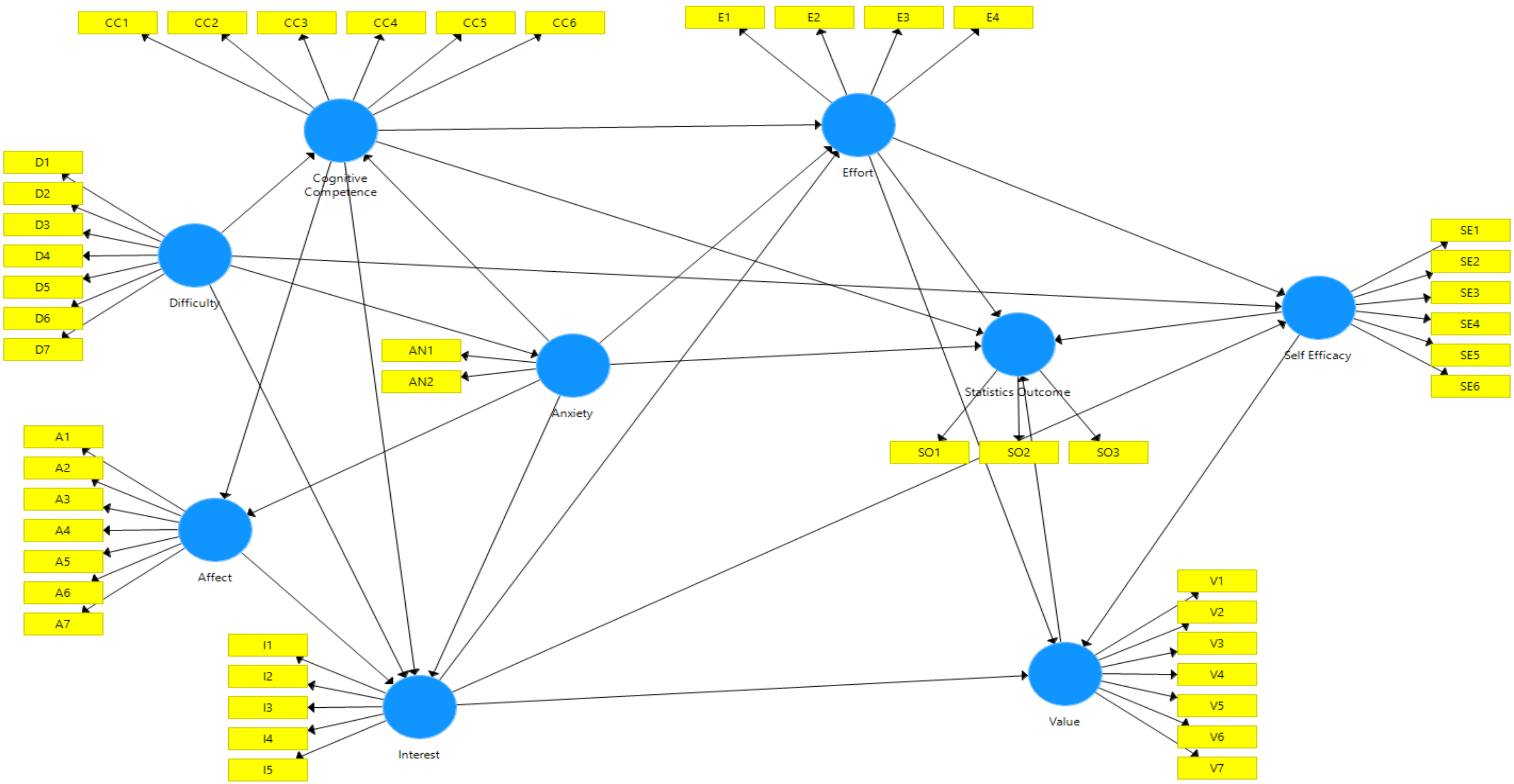

Figure 1.1: Hypothesised Structural Model (adopted from Ghulami et al., 2014:12)

1.5 Significance of the study

It is expected that the study will contribute to the current body of literature by suggesting ways to avert negative attitudes and promote positive perceptions. By testing structural relationships, both moderated and mediated, it is expected that this study would contribute to the literature in general by investigating the causal links, if any, and any existing relationships among perceptual and attitudinal factors. The results of the study would give an indication of basic constructs that need the instructors' attention. These constructs may be developed in students or used to improve instruction of the statistics subject to ensure students' achievement in related statistics courses. The study will serve as a guide to redesign programmes for statistics for non-majors and for the faculty to relook the entrance requirements for degree programmes offered, and pay more attention to how students learn statistics first rather than focus on the pedagogical content of the subject.

Attainment of the aforementioned goals could be instrumental in overall statistics course achievement and long-term retention of statistical concepts and consequently increased post-graduate intake at the NWU, specifically the Faculty of Commerce. This study will contribute to the South African literature and to the development of a suitable statistics curriculum, should the need arise, and it will serve as a launching pad for future studies. It is a widely known fact that statistics is an important tool for a variety of commerce, administration, and some natural science disciplines. For this reason, the current study will make a significant contribution to the advancement of SEM and its possible application in other disciplines. Finally, one implication that can be drawn from this relates to the importance of redesigning classroom activities so that it will aid in enhancing students' self-concept and self-efficacy.

1.6 Ethical considerations

An ethical clearance form was submitted to the relevant committee through the supervisor. All ethical considerations were strictly adhered to in the administration of the questionnaire. Anonymity and confidentiality were preserved in that the participants were volunteers who could withdraw from the study at any time and with no ramifications.

1.7 Study Organisation

Chapter 2 focuses on the literature review for this study: the theoretical framework, results, findings and recommendations of related studies, recent and ongoing researches on structural equation modeling application on students' attitudes and perceptions on statistics. The chapter attempts to trace the origin, use, evolution, and the importance of PLS over other multivariate techniques such as exploratory factor analysis (EFA), confirmatory factory analysis (CFA), covariance-based (CB-SEM), multiple regression analysis (MRA) in research.

Chapter 3 thoroughly looks into the research design; methodology to be followed as well as suitable reliability and validity tests and procedures, as well as the statistical package to be used in analysis of the data. The chapter's main focus is the research design: data, model specification, measurement instruments, multivariate assumptions, e.g., variable selection, sample requirements, model estimation and assessment of model fit using fit indices.

Chapter 4 focuses on statistical analysis and interpretation of results, and presents outputs in tabular or graphical form. Model fit assessment, based on output results, will be done. The output was compared with critical or benchmark values in order to select a final parsimonious and spurious-free model.

Finally, *Chapter 5* presents the findings, concluding remarks and recommendations to the affected parties mentioned in the study, that is, students and the Faculty of Commerce and Administration at the university. These are based on results in chapter 4 of this study.

1.8 Summary

This chapter attempted to give a synopsis of the application of the SEM application in students' attitudes towards the statistics subject. It looked at the emergence of SEM, its limitations and its application throughout the past century and its relationship with other statistical techniques. The introduction of PLS methodology was made, aiming the at the limit of SEM to actually capture its shortfalls, which include non-normality and sample size, and look how it can be used to cure SEM deficiencies. The hypothesized structural model was introduced on the basis of existing theory. The model is based on existing theory or literature. The research questions, objectives and hypothesis emanated from theory and aim to attempt to bridge the SEM methodological gap. Furthermore, the significance and contribution of the study was outlined herein.

Chapter 2

Theory and literature review

2.1 Introduction

This chapter seeks to provide the background to and evidence of the application of the two methodologies. Firstly, a brief history on the development of SEM and PLS methodologies, their application, and advancement is discussed. Secondly, the theoretical framework of SEM and PLS is briefly looked into; this includes the objectives and limitations of these methodologies. This overview is not limited to the utility of structural equation modeling (SEM) and the lesser known and less utilised PLS in modeling students' perceptions and attitudes towards statistics subject only. Finally, the chapter deals with related literature on students' perceptions and attitudes. Model fit indices are introduced in brief and discussed later in Chapter 3. The primary technique to be used is SEM, with PLS as a potential substitute or remedial tool.

2.2 Theoretical framework

Statistics courses are not only a terrible experience to the majority of non-majors, they also pose a threat to completion on time of their degrees (Onwuegbuzie & Wilson, 2003). Bad experiences are often a precursor to debilitating statistics anxiety effects on academic achievement, anxiety which emanates not from a lack of proper instruction or training, and insufficient skills, but students' misperceptions and little or no proper mathematical background is contributory if not intermediary in students' achievement in statistics (Hulsizer & Woolf, 2009; Pan & Tang, 2004)).

Anxiety inducing factors are classified into three categories according to Baloğlu (2003) such as dispositional, course-related or situational, and person-related factors. Moreover, dispositional factors are emotional and psychological traits of students which include their perceptions, attitudes, and mathematical self-concepts according to Baloglu (2003) and (Dykeman, 2011). 'Situational factors' (e.g. Onwuegbuzie & Wilson, 2003; Pan & Tang, 2004 and 2005; Dykeman, 2011) are dependent on whether the course is a mandatory course or an elective one, prior knowledge of statistical course and mathematical content.

There is a growing body of research describing the relationship between students' attitudes towards statistics and statistics achievement (Emmioğlu & Çapa-Aydın, 2011; Sorge & Schau, 2002). Most studies focus on one aspect at a time and do not explore covariation or causality. This study attempts to address this gap. A meta-analysis study of students' attitudes toward statistics by Emmioğlu & Çapa-Aydın (2011) has cited positive relationships between *affect* and *perceived cognitive competence* and course grade. It also found that course *value* has a small but positive effect on *perceived difficulty.*

An array of construct relationships has been described in existing literature, among others (1) the positive effects: of *affect*ion *perceived cognitive competence* and *course grade*, (2) of *mathematics self-concept* on *interest, difficulty* and *cognitive competence,* (3) of *value* on course grades, usage of real-life or career-aligned problems, and (4) of *future use of statistics* on *interest, cognitive competence, value* and *difficulty*. It is evident that with a high correlation between mathematics and statistics (Onwuegbuzie & Wilson, 2003;Onwuegbuzie, 2004) statistics anxiety may possibly be born from existing and prevalent mathematics anxiety oftentimes accompanied by negative expectations.

Many scholars and educators believe that negative perceptions and attitudes towards statistics are important in a student's academic life. It is for this particular reason that Schau (1995); Dauphinee, Schau and Stevens (1997) and Schau (2003b) developed SATS-28 (with four constructs) and later SATS-36 (with six constructs). The instruments' constructs are congruent with Eccles' Expectancy-Value Model's (EVM) theoretical framework (Wigfield & Eccles, 2002; Eccles, O'Neill &Wigfield, 2005). This model is designed to explain why students perform differently in different academic domains. Wigfield and Eccles (2002) and Eccles, O'Neill and Wigfield (2005) suggest that students' Expectation for Success (ES) and their Subjective Task Value (STV) are related. They further theorised that students' achievement outcomes are predicted by their ES and STV.

Students are prone to engage in or select tasks that they have attached some value according to the EVM theory. The EVM includes, among other factors, Stable Child Characteristics and Previous Achievement-Related Experiences. STV is made up of the factors: (a) Cost, (b) Utility Value, (c) Intrinsic Value, and (d) Attainment Value. Cost may be referred to students' avoidance of a task, fear of failure, mathematics anxiety (due to equations), and task difficulty. Utility Value refers to the links the worth of statistics tasks to the students' careers. Intrinsic Values is the students' interest in statistics or enjoyment from doing and completing statistical tasks. Lastly, Attainment Value is the importance students attach to tasks. According to the EVM, ES are positively influenced by Attainment, Utility and Intrinsic Values. Conversely, ES are negatively influenced by Cost. On the other hand, ES influences Attainment, Utility, Intrinsic and Cost Values positively. Wigfield and Eccles' (2002) study reported that further course enrolment is predicted by two components, that is, ES and STV.

According to Durik, Vida and Eccles (2006) study it has been reported the Interest and Value that fourth-grade learners attached to reading predicted English courses that they would consequently enrol for in high school. Another study showed that mathematics and science tasks in late elementary (primary) school predicted further mathematics and science enrolment in high school. Although much research focus has been based on primary school learners and high school learners, this study asserts that the EVM theoretical framework can assist in understanding attitudinal and motivational factors of university students who enrol for statistics courses. The EVM seeks to explore links among its factors, especially Achievement-Related choices by students and the Utility Value of statistics as a subject.

Of interest to note is how Eccles' EVM is consistent with SATS-36 six components and other variables from the MPSP, emphasizing the multidimensionality of perceptions, attitudes and motivation. The framework aids instructors and researchers alike to determine the factors that directly or indirectly affect the perception and attitudes of students toward statistics, their achievement related choices and the relationships among them. According to Ramirez, Emmioglu and Schau (2010), SATS-36 complements Eccles' EVM by demonstrating that some of the constructs are relevant to university students' statistics course. The EVM further allows for researchers to determine the interrelation between attitudinal and motivational factors, suggests (Ramirez *et al*. 2010). The EVM allows for an extension into statistics and mathematics domain or other academic domains.

The EVM has been acknowledged as an appropriate instrument and theoretical framework- with its implications in pedagogy, evaluation and research, for investigating the complexity of students' perceptions and attitudes toward statistics subject. The consistency between the EVM and SATS-36 and selected variables from the MPSP is presented in Table 2.1. Ramirez *et al*. (2010) suggest that when selecting an instrument, instructors and researchers aiming to measure students' perceptions and attitudes towards a statistics subject should consider SATS-36. This is due to its consistency with the EVM and it psychometric properties (Hilton, Schau & Olsen, 2004; Tempelaar, Van der Loeff & Gijselaers, 2007).

Another model of interest is the Statistics Attitudes-Outcome Model (SAOM) as cited in Ramirez, Schau and Emmioglu (2012); Emmioglu and Capa-Aydin (2012) and Arumugan (2014). The latter applied the PLS algorithm to confirm the SAOM. The SAOM is also said to be congruent with many learning theories as it assumes that affective factors, besides cognitive factors play a pivotal role in the students' statistics outcomes attainment. The model is based on the Self-Efficacy theory (Bandura, 1977; Pintrich, 2003; Wigfield, Eccles, Schiefele, Roeser & Davis-Keane, 2006), Self-Determination Theory (Deci & Ryan, 2002; Wigfield *et al.*, 2006), and The Theory of Planned Behaviour (Bohner & Wanke, 2002; Ajzen, 2005). The items of the planned behaviour congruent to components of SAOM are presented in Table 2.2. SAOM components corresponding to Eccles' EVM are presented in Table 2.3.

In their study "The Importance of Attitudes in Statistics Education", Ramirez, Schau and Emmioglu (2012), suggest the following model in Figure 2.1. The constructs in their model emphasize the multidimensionality of students' attitudes and Course Outcomes. The model suggests that Previous Achievement-Related Experiences are influenced by Student Characteristics. Students' Statistics Attitudes are impacted by both. Statistics Course Outcomes are influenced by all three. Previous Achievement-Related Experiences may have an impact on the students' Statistics Attitudes, and together these may result in different Statistics Outcomes.

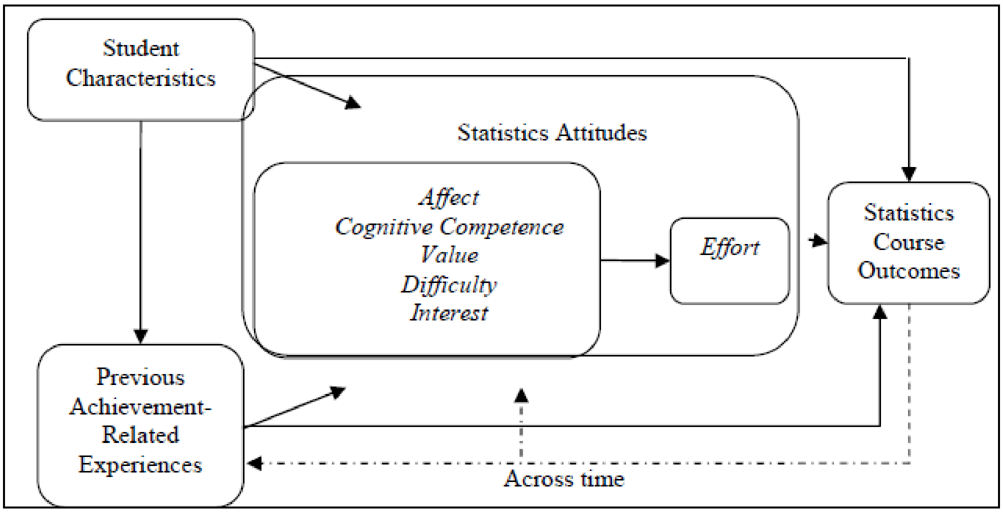

Figure 2.1: Students' Attitudes toward Statistics - Model (SATS-M) (Ramirez, Schau and Emmioglu, 2012)

Table 2.1: Similarities between SATS-36/MPSP and the EVM constructs

SATS	**EVM**
Affect	Affective Reactions & Enjoyment Value
Cognitive Competence	Self-Concept of One's Abilities & Expectations of Success
Difficulty	Perception of Task Demands
Value	Attainment and Utility Values
Interest	Intrinsic Value
Effort	Cost
Additional constructs	
MPSP	**EVM**
Achievement	Previous Achievement-Related Experiences & Interpretations of Experience
Self-Efficacy	Task Demands

Table 2.2: Congruence between SAOM components to The Theory of Planned Behaviour

SAOM Components	Theory of Planned Behaviour Components
Attitudes	Attitude toward the Behaviour
Cognitive Competence	Perceived Behavioural Control
Effort	Behavioural Intention
Statistics Outcomes	Behaviour

Table 2.3: SAOM Components congruent to Eccles' EVM

SAOM	**Eccles' EVM**
Mathematics Achievement	Previous Achievement-Related Experiences
Affect	Affective Memories & Intrinsic Value
Cognitive Competence	Self-Concept of One's Abilities & Expectations of Success
Value	Attainment and Utility Values
Difficulty	Perception of Task Demand
Interest	Interest-Enjoyment Value
Effort	Cost
Statistics Outcomes	Achievement-Related Choices and Performance

2.3.1 Emergence of Structural Equation Modeling

Most statistical methods are only suited to model simple relationships, e.g. correlations and regression analysis, analysis of variance (ANOVA) or multiple analyses of covariances (MANCOVA), and so on. Though correlations are the basis of exploratory research, they can only be used for non-causal exploration of the relationship between constructs, and on which a future path model, causal links, and provision of measurement models studies may be based (Privman *et al.*, 2013). It is for this reason that a statistical technique capable of providing path models for confirmation of pre-existing theories, development and determination of new theories is employed. Structural Equation Modeling has the ability to determine the underlying latent constructs' structure, their underlying causal links, amongst latent constructs and individual variables, as well possible covariation of the aforementioned variables and constructs, is used (Lowry & Gaskin, 2014).

SEM is used instead of hierarchical or stepwise uses of conventional multiple analyses of variances (MANOVA) or (MANCOVA), multiple regression. It combines qualities of both exploratory and confirmatory factor analysis as it does these simultaneously. To determine the network of such relationships, links, and models, a more robust statistical technique with all the capabilities of all the aforementioned statistical techniques is employed. Causal models refer to how the variation of one or more variables results in the variation of the other variable(s) within a given framework.

Three primary assumptions are made by causal inference: (1) covariation, (2) temporal precedence, and (3) absence of spurious relationships (Lowry & Gaskin, 2014.). Covariation refers to bivariate change between predictor and criterion variables. Temporal precedence is when a predictor variable occurrence precedes that of the criterion variable, such that the link of the two is truly causal. Absence of spurious relationships is when mediator variables or confounds are accounted for in the model. SEM tests, simultaneously, the validity of measures in a model and plausibility of theory (Chin, 1998; Gefen, Straub, & Boudreau, 2000). Correlations, multiple regression, etc., cannot test for instrument convergent, discriminant, and nomological validity simultaneously, thus researchers have to follow a 'two-step approach' (Gefen*et al., ibid.*). It is for this reason that the SEM method of analysis is followed for this study, as it also offers a solution to the two-step approach (Chin, 1998), with its capability to test convergent validity and discriminant validity simultaneously (Chin, 1995), reduce the likelihood of false negatives (Type 2 errors) (Chin, 1998) and better tests moderators (Lowry & Gaskin, *ibid.*).

An SEM model including measures of mathematical aptitude, statistics anxiety and attitudes, motivation to learn statistics, and effort was tested by (Lalonde & Gardner, 1993) in predicting statistics performance. The study found that there was a direct positive relationship between aptitude and performance, as well as the negative of statistics anxiety, which in turn appeared to be positively related to both motivation and performance. The study found that the path from statistics anxiety to performance was non-significant. In a replicated study by Tremblay, Gardner and Heipel (2000), contrary to the expected outcome, there was a significant and negative relationship between statistics anxiety to performance, and a negative path from attitudes to anxiety. Another relevant work is the Anxiety-Expectation Mediation (AEM) model (Onwuegbuzie, 2003) where both statistics anxiety and achievement's expectation were expected to mediate the relationship between cognitive, personality, and person characteristics, and performance.

Statistics anxiety and achievement played a pivotal and significant role in mediating the relationship between performance and research methodology anxiety, study behaviour, course load, and the number of statistics courses taken in an academic year. (Nasser, 2004) study obtained a high positive effect of mathematical aptitude and a lower, but significant, positive effect of attitudes on performance with a SEM approach. Anxiety was also found to be directly and negatively linked to attitudes and the path between anxiety and performance was non-significant, consistent with Lalonde and Gardner (1993), but in contrast with Onwuegbuzie's (2003) and Tremblay *et al.* (2000) studies.

Chiesi and Primi (2010) proposed an SEM model where mathematical background affects both mathematical knowledge and attitudes toward statistics. These two variables influenced statistics anxiety, which in turn was directly related to attitudes and performance. A direct effect from mathematical knowledge to performance was also evident. The study took into account potential changes in attitudes during the course due to the interaction with the contents and the requirements of the discipline, and whether this change was mediated by initial mathematical competence. The results showed that both post-test attitudes and mathematical knowledge were directly and positively related to performance, but anxiety only indirectly affected performance through attitudes. They aimed to investigate the relationships between math background, trait anxiety, test anxiety, statistics anxiety, attitudes toward statistics and statistics performance in a sample of 472 university students enrolled in statistics courses of Health Sciences majors.

The SEM approach showed the attitudes as the stronger direct predictors of performance, and played a full mediating role in determining the relationship between statistics anxiety and performance. Contrary to the hypothesized model, the direct contribution of math background, trait anxiety, and test anxiety to performance was non-significant. A final model exhibited a direct positive effect on performance by attitudes, and in turn attitudes were positively influenced by math background and negatively affected by anxiety. Math background also appeared as a negative predictor of anxiety. Finally, test anxiety was a positively direct predictor of statistics anxiety.

Pearson (1901) laid the foundations for principal components analysis, which was followed by Spearman's (1904) contribution to factor analysis. The factor analysis technique pioneered by Spearman (*ibid.*) proved instrumental in the development of structural equation model. For the full account of the history of path analysis and structural equation modeling, see Denis & Legerski (2006). Causal modeling dates to Wright (1918, 1921). Wright invented path analysis in order to estimate the magnitudes of effects when the basic causal pathways were already known (e.g. genetics). That is, given a true causal model, the technique of path analysis could be applied to estimate it for observed variables. The foundations of SEM are rooted in classical measured variable path analysis (Wright, 1918) and confirmatory factor analysis (Jöreskog, 1966, 1967). The development and use of SEM extends as far back as the first half of the twentieth century.

SEM was developed by geneticists and economists with the desire to be able to establish causal relationships (Wright, 1921; Blalock, 1962; Wold, 1966). Structural equation modeling is an important statistical tool in economics and behavioural sciences, and has recently been applied in information systems and marketing research. The structural models express relationships among either directly observable variables (manifest variables) or latent variables (constructs). The reader is referred to Long (1983), Loehlin (1987), Bollen (1989b) and Everitt (1984) for an introduction to latent variables. For more insight on recent developments and advancements in structural equation modeling the reader is referred to, for an example, Hoyle (2012); Khine (2011) and Duncan (2014).

The measurement model (factor analysis) and structural equation modeling (path analysis) approaches were then integrated into a framework that Bentler (1980) called the JWK model (named after three authors: Jöreskog, Keesling & Wiley) and developed by Jöreskog and Sorbom (1976). LISREL was one of the first widely available computer programmes able to analyse models based on the JWK framework. Another major development had to do with the adaptability of SEM and other multivariate techniques for multilevel (group) analysis, which are applied in data sets where scores (cases) are grouped into higher-order units, such as siblings within families (Muthén, 1994). Table 2.4 below gives a historical overview of SEM:

Table 2.4 History of SEM and its precursors

Pre-computer	**Computer Intensive**	**A priori system of equations**	**Purpose**
Exploratory Factor Analysis **Lawley (1940)**	Factor Analysis (PCA) through iterative OLS **Wold (1966)**	PLS analysis through iterated OLS **Wold (1978)**	Prediction
Path analysis **Wright (1921)**	Confirmatory Factor Analysis **Jöreskog (1969)**	LISREL-SEM **Jöreskog (1969)**	Model Confirmation
Systems of Linear Equations Estimation **Koopmans (1950)**	Instrumental Variables and 2SLS **Theil (1953)**	3SLS and full-information regression SEM **Zellner (1962)**	Model Confirmation/Prediction

The SEM approach use has been widespread interest in recent years. This ranges from fields such as information systems, marketing research and business management. SEM and PLS literature includes (Blalock, 1961a & 1969; Jöreskog, 1973; Chin, 1998; Ullman & Bentler, 2003; Haenlein & Kaplan, 2004; Henseler, Ringle & Sinkovics, 2009; Hair, Ringle & Sarstedt, 2011, 2012 & 2015); Hair *et al.*, 2012a, 2012b & 2013; Bollen, 2014; Dijkstra & Henseler, 2015; Henseler, 2015. A number of indices have been developed over time to assist the researcher to select the best structural model. The following indices in Table 2 are some of the benchmarks used in SEM and PLS alike. All indices' origin, application, adoption by this study and their evolution are documented in detail in Chapter 3.

Model Fit Indices

A model of best fit is recognized by looking at individual fit indices for each model during analysis. Several types of these indices have been distinguished by many authors in the last thirty decades (see Mulaik *et al.*, 1989; Bentler 1990; Tanaka 1993; Byrne, 1998; Maruyama, 1998), among others. The ability of the hypothesized or *a priori* model to reproduce the covariance structure of variables of interest is assessed by *absolute fit indices* (McDonald & Ho, 2002). The other batch of indices is concerned with the ability of the hypothesized model to account for the sample data relative to a restricted model which is less complex, are called *comparative* (Miles & Shevlin, 2007) *or incremental fit indices.* The final batch selects or identifies better fit of a model by an increment of the number of estimated parameters. These are termed parsimonious fit indices. The other criterion measures deemed useful for comparing models with a varying numbers of parameters were also introduced, namely, the Akaike's (1987) information criterion (AIC) and Schwarz's (1978) Bayesian criterion (SBC).

Other measures of goodness of fit range approximately from zero to one: these include the parsimonious fit index (James, Mulaik, & Brett 1982), the adjusted goodness-of-fit index (AGFI) (Jöreskog & Sörbom 1988), and the centrality measure (McDonald Centrality) (McDonald 1989) which is > 3.0 in most cases. Steiger and Lind (1980) proposed the root mean squared error approximation (RMSEA), which measures the discrepancy between the fitted model and the inferenced covariance matrix of the population. RMSEA value falls within a certain specified confidence value. Browne and Crudeck (1993) proposed the expected cross validation index (ECVI) that measures a model's ability to predict future sample covariances. The fit indices are presented in Table 3.4 in Chapter 3.

2.3.2 Relevance of Structural Equation Modeling

Structural equation modeling (SEM) is defined by Wright (1921) as a statistical method used to test and estimate causal relationships by assuming causality (Bartholomew, 2002). Before learning about SEM, one should have a good understanding of (1) data screening techniques, (2) the principles of *multiple correlation/regression*, and (3) the correct interpretation of results from model fit indices and statistical tests. Statistical results in SEM are interpreted the same as regression coefficients in multiple regression (MR). Both confirmatory and exploratory modeling can be used by SEM. In other words, SEM is suitable for both theory testing and theory extension. The potential for bias, which may be due to the omission of a predictor that is significantly correlated with others in the equation, is basically the same in SEM and MR. MR plays an important role in exploratory data analysis.

There are a number of statistical tests in SEM, and their correct interpretation is essential. The term *structural equation modeling* (SEM) does not designate a single statistical technique but refers to a family of related statistical procedures. Terms such as *covariance structure analysis, covariance structure modeling,* or *analysis of covariance structures* are used in the literature to classify these techniques under a single label. These terms are essentially interchangeable. SEM requires of the researcher to provide a lot of information about: (1) which variables are assumed to affect others, and (2) the directionalities of these effects. These *prior* model specifications reflect the researcher's hypotheses, and in total they make up the model to be analysed. In this sense, SEM can be viewed as a *confirmatory technique*. That is, the model is a given or specified at the start of the analysis, and one of the main questions to be responded to is, whether it is supported by or fits the data. As often happens, the data may be inconsistent with the model, which means that the researcher must either abandon the model or simply modify the hypotheses on which it is based (Kline, 2011; Hair *et al*., 2010)

The modified model is then tested again with the same sample data (Jöreskog, 1993). The goal of this process is to "discover" or "develop" a model with three properties: (1) it makes theoretical sense, (2) it is reasonably parsimonious, and (3) its correspondence to the data is acceptably close. Hair *et al.* (2011) suggested that every other structural equation model is distinguished by the following characteristics: (1) estimation of multiple and correlated dependence relationships, (2) an ability to represent latent concepts in these relationships and account for variance in the estimation process, and (3) defining a model to explaining the entire set of relationships.

SEM has the ability to simultaneously specify the structural model and estimate a series of all hypothesised, interdependent and multiple path equations (Hair *et al.*, 2010). Theory, an *a priori,* and research objectives form the basis for which the variables in the researchers' data are dependent or independent. SEM also has the capability to have the dependent variable in one relationship to be the independent variable in the other subsequent relationships. This gives rise to the interdependent nature of SEM. The hypothesized relationships are, at the end of the analysis by a statistical program, translated to a series of structural equations for each dependent variable (Hair *et al.*, 2010). From a theoretical perspective, most concepts are not unidimensional and are relatively complex in nature. Moreover, SEM provides a measurement model which enables the researcher to have one independent or dependent construct measured by a set of observed (manifest) variables, and constructs (outcome variables) alike.

SEM models are often depicted by visual diagrams with coefficient on the paths representing either of the following: weights, coefficients, and loadings, direct and indirect effects. The diagram, also called the model, can be altered or re-specified multiple times until theory is proven and the resulting construct are discriminatorily and nomologically valid. The reader is referred to (Cronbach & Meehl, 1955; Peter, 1981; Bollen, 1989; Nunnally & Bernstein, 1994; Tian *et al.*, 2001; Liu, Li & Zhu, 2012), for more insight on the subject of nomological validity. The following relationships can be measured: (a) between a construct and a measurement variable, (b) between a construct and multiple measured variables (reflective or formative), (c) between two constructs (dependence or structural relationship), and (d) between constructs (correlational relationship).

Nomological validity involves four models as cited in Liu, Li and Zhu (2012): (a) the group factor model (first-order construct model, with a single level of correlated constructs) (Rindskopf & Rose, 1988), (b) second-order model (several first-order constructs correlate due to a single second order construct) (Rindskopf & Rose, *ibid.*), (c) extends the group factor model and forms path between several first level constructs, and (d) an extension of the second-order model (second-order construct mediates the relationship between several first-order constructs).

2.3.3 Variables in Structural Equation Modeling

There are two main classes of variables in SEM, namely, observed and latent. The observed class represents the raw data—that is, variables for which one has collected scores and entered them in a data file (Kline, 2011). Another term for observed variables is *manifest variables*. Observed variables can be nominal, ordinal or continuous, but all latent variables in SEM are continuous. There are other statistical techniques for analysing models with categorical latent variables. Latent variables in SEM correspond to the conceptual or hypothetical constructs or factors, which explanatory variables are presumed to reflect a continuum that is not directly observable. An observed variable used as an indirect measure of a factor is referred to as an *indicator*.

The explicit distinctions between a factor (construct) and an indicator in SEM allow one to test a wide variety of hypotheses about measurement (Kline, 2011). Error terms in SEM can be associated with either observed variables or factors specified as outcome (dependent) variables. A residual term represents *variance unexplained* by the factor that the corresponding observed variable or indicator is supposed to measure. *Random measurement error* or *score unreliability* is the main cause of unexplained variance (Kline, 2011). It has similarities to multiple regression, or multi-level multiple regression, since relationships for each endogenous (dependent) variable can be written in a form similar to a regression equation (Hair *et al*., 2010). SEM requires sample sizes similar to most multivariate techniques. A typical sample size in studies where SEM is used is about 200 cases (Kline, 2011). This number of cases corresponds to the approximate median value of sample sizes used in surveys of published articles in which SEM results are reported. Earlier reviews by Breckler (1990) and a more recent review by Shah and Goldstein (2006) in personality and social psychology management science journals, respectively, are examples.

Missing data often give biased results and false conclusions about the structural model. Structural equation modellers are in a particularly advantageous position for using maximum likelihood estimation (MLE) for handling missing data. Even when the data are not missing at random, methods that assume missing at random (MAR) can often produce good results, at least much better than conventional approaches can (Sinharay *et al*., 2001). Furthermore, SEM allows for relationships where the endogenous variable is exogenous (independent) in other relationships, can be estimated simultaneously. A variation of this technique can be used in place of other dependence techniques such as; MANOVA, non-metric, and even categorical variables model. SEM is also similar to confirmatory factor analysis (CFA) where the measurement model is specified from the onset, that is, which specifies which manifest variables are associated with which construct.

It is for the reasons stated above that SEM, specifically maximum likelihood or covariance-based SEM should not be attempted without a strong theoretical basis, for both the initial specification of the measurement and structural models. SEM is thus not applicable for use where theory is absent or limited; it is only suitable for theory justification objectives. Another term that is worth our attention is *causal modeling*, which is a somewhat archaic expression first associated with the SEM technique of *path analysis*. The results of an SEM analysis cannot be taken as evidence for causation. Wilkinson and the Task Force on Statistical Inference (1999, p600) noted that use of SEM computer software "rarely yield results that have any interpretation as causal effects". This assertion has prompted many researchers to develop a statistical technique that not only is applicable when theory is weak, compute direct and indirect effect, but also can determine causal effects and correct model misspecification regarding formative and reflective latent variables.

Hair *et al.* (2010) and Kline (2011) suggested that SEM is not a causal testing technique. It would require experimental or longitudinal data for causation to be established, and some controlled manipulation as in MANOVA or ANOVA. SEM may treat dependence relationships as causal if the following four established as evidence are reflected in the SEM model (DeVellis, 1991; Jarvis *et al.*, 2003): (1) covariation, (2) sequence, (3) non-spurious covariation, (4) and theoretical support. Covariation is the establishment of a change in a cause brings about a corresponding change in effect, that is systematic covariance between cause and effect is necessary. "Statistically significant estimated paths in the structural model provide evidence of covariation"; as suggested by (Hair *et al.*, 2010:644). Sequence or temporal sequence of events is also a necessary element in establishing causation. Non-spurious covariance is the presence of the size and nature of the relationship between a cause and an effect, and should not be affected by the inclusion of other constructs (or variables) in an SEM model.

An event included in the analysis actually does not explain both the cause and effect (Hair *et al.,* 2010). When collinearity is not absent, the researcher comes close to reproducing conditions of an experimental design. SEM, unfortunately, involves predictors or constructs which exhibit multicollinearity with other predictors and the construct. This limitation of SEM has led researchers (Wold, 1966; Wold, 1973; Wold, 1982; Barclay *et al*., 1995; Chin, 1998a; Chin, 1998b & Wold *et al*., 2001) to develop a technique with causation establishing capabilities. Partial least squares analysis or variance-based SEM is such a technique.

2.3.4 Structural Equation Modeling Application

Misperception of statistics may give rise to consistent and increased avoidance of the subject. Statistics-related stress develops this avoidance, or poor performance on the subject. Cherney and Cooney (2005) in their study revealed that the lower the mathematics and statistics perceptions, the lower the final grade. Students' misperceptions about both statistics and their mathematical skill (or lack thereof) are due to anxiety and do not necessarily emanate from their limited skills or bad instruction received (Pan & Tang, 2004; Onwuegbuzie& Wilson, 2003). Thus statistics anxiety may lead to academic procrastination in students (Onwuegbuzie, 2004). Contrary to expectation, Slootmaeckers' (2012) study of 630 students in first year, 39 in second year, 41 in third year and 116 in master's programmes, using Schau *et al.*'s (2003) SATS-36 survey instrument, found that first-year students with regards to interest in learning statistics achieved lower grades.

The study further found that mathematical self-concept was related positively to number of mathematics classes taken in high school, and found students' attitudes toward difficulty of statistics were related to better long-term retention of statistical skills. This may be due to the fact that attitudes develop and change through one's academic life. In another study (Coetzee & Van der Merwe, 2010) using a cross-sectional survey design, to a sample of 235 industrial and organisational psychology students at a university in South Africa. Confirmatory factor analysis was employed to test the validity of the SATS-36for the sample. The findings revealed that although students perceived statistics to be complicated, difficult and technical, they are interested in learning the subject as they also believe it to be a valuable instrument in their careers of choice as a professional tool. Students who had high mathematics self-efficacy also had high statistical self-efficacy. The study suggested that students' mathematics self-perception could be managed in preparing students for statistics.

Coetzee and Van der Merwe (*ibid*), found no significant correlation between students' attitudes toward statistics and the number of years they had studied mathematics at high school, or the number of mathematics courses they had previously taken at university. The study went on and found that there was a significant correlation between students' perception of their statistics and mathematics competence. The study widely suggested that students who exhibit negative attitudes and aversion after taking a statistics course will most probably never use it again. Schau and Emmioglu (2012) recommend that instructors attempt to sway students' attitudes for the better. Extrinsic factors affecting students' attitudes towards statistics should be studied (Coetzee & Van der Merwe, 2010). This may range from students' past mathematics education and performance, study behaviour, class size and the instructor himself.

As outlined earlier in chapter 1, most of the studies outlined have focused primarily on "simple" relationships between attitudes and achievement but have not estimated structural model (Dempster & McCorry, 2009). Most researchers have focused solely on measuring students' attitudes and perceptions and how these impede on students' course achievement and not the underlying complex structural model. Their objective was to determine, validate and check the reliability of the structure of constructs. The study seeks to determine the constructs with a view to determine the relationships between them and variables that form them, and their eminent malleability. Statistics anxiety and achievement mediated the relationship between performance and research methodology anxiety, study behaviour and course load, among other variables. The desire to test complete theories and concepts is one reason for authors to embrace SEM (Bollen, 1989; Henseler *et al*. 2009).

Nasser's (2004) study obtained a high positive effect of mathematical aptitude and a lower, but significant, positive effect of attitudes on performance with a SEM approach. Anxiety was also found to be directly and negatively linked to attitudes and the path between anxiety and performance was non-significant, consistent with Lalonde and Gardner (1993), but in contrast with Onwuegbuzie's (2003) and Tremblay *et al.'s* (2000) studies. Chiesi and Primi (2010) proposed an SEM model where mathematical background affects both mathematical knowledge and attitudes toward statistics. These two variables influenced statistics anxiety, which in turn was directly related to attitudes and performance. A direct effect from mathematical knowledge to performance was also evident. They took into account potential changes in attitudes during the course due to the interaction with the contents and the requirements of the discipline, and whether this change was mediated by initial mathematical competence.

They aimed to investigate the relationships between math background, trait anxiety, test anxiety, statistics anxiety, attitudes toward statistics and statistics performance in a sample of 472 university students enrolled in statistics courses of Health Sciences majors. SEM approach showed the attitudes as the stronger direct predictors of performance, and played a full mediating role on the relationship between statistics anxiety and performance. Budé *et al.* (2007) focused on motivational constructs and their effect on students' achievement in a statistics course. The study employed a questionnaire to measure students' several motivational constructs, all with respect to statistics. The study found, using an SEM approach, outcome expectancy as negative, and affect towards statistics as negative and limited study behaviour led to unsatisfactory achievements. Path analysis confirmed causal links in a model that was based on attribution (Pintrich, 2000) and learned helplessness (Peterson, 1993) theories.

In a study aimed at finding the impact of engineering students' attitudes on achievement in statistics, using the structural equation modeling approach, Sorge and Schau (2002) found the following: (1) baseline model results showed that the indicator variables represented the constructs well, (2) The data fit both the Saturated and Pruned Statistics Attitudes-Achievement Models reasonably well, (3) the Pruned model was more parsimonious, thus was the more preferable of the two, (4) no relationship between value and achievement, (5) the results suggested a complex relationship between difficulty and value, with the direct effect large and negative, and (6) paths from previous success to difficulty, affect, and value, as well from difficulty to affect and achievement, and one from cognitive competence to value were not statistically significant. These paths were eliminated from the Saturated Model to form the Pruned Model.

2.4 Partial Least Squares Modeling applied to perceptions and attitudes

Partial Least Squares based modeling provides researchers with a platform that enables them to perform analysis particularly suited to situations where constructs (latent variables) are measured by a very large number of indicators (manifest variables), and where a maximum likelihood covariance-based SEM (CB-SEM) tool reaches its limit in analysis. It is also used primarily when there is little or no *a priori* information. PLS objective is to optimize the variance of the criterion variables explained by the predictor variables instead of producing the empirical covariance matric. PLS relates information presented in two tables that collect information on the same set of observations. PLS has two main components, namely PLS Correlation and PLS Regression. The former intends to generalize the idea of correlation of two variables to two tables (Abdi & Williams, 2000). This technique can easily handle large sets of data and sophisticated experimental designs. The main goal of PLS Correlation is to determine pairs of latent vectors with maximal covariance.

PLS Regression's main objective on the other hand is to predict a set of variables from a set of predictors, as well as multicollinear predictors. This technique aims to find a series of latent variables such that the covariance between them and predictors is maximal, and as such, latent variables should be uncorrelated with each other. PLS can readily examine interaction effects with numerous variable levels, and can cope with relatively small sample sizes (Gefen *et al*., 2000). PLS was developed as an alternative to covariance-based SEM that would emphasize prediction power while simultaneously relaxing the demands on data distribution and specification of relationships (Dijkstra, 2010). Estimating models via a series of ordinary least square (OLS) regression implies that PLS relaxes the assumption of multivariate normality needed for maximum likelihood based SEM estimation (Hwang, 2010; Dijkstra, 2010).

Furthermore, it has a generally higher statistical power (Reinartz, Haenlein, & Henseler, 2009) and is not constrained by identification concerns, even if models become complex, a situation that typically restricts CB-SEM usage (Hair, Ringle, & Sarstedt, 2011). PLS analysis original purpose is prediction in research contexts with rich data but weak theoretical framework and theory. The result of this technique are robust if data are highly skewed (Henseler, Ringle, & Sinkovics, 2009). It is for the reasons stated above that Structural Equation Modeling with Partial Least Squares Analysis approach is followed in this study. The application of partial least squares, also called variance-based SEM, and has seen much popularity in the past decade. The reason could be the relaxed multivariate strict assumptions, especially of sample size and distribution. PLS exhibits high levels of statistical power; no identification issues with small samples sizes and no distributional assumptions since it is a non-parametric regression-based estimation method (Henseler *et al*, 2012).

If the focus is much more on prediction rather than explanation, PLS could be beneficial for achievement driver studies in learning and application (Hair *et al*., 2011a). The technique incorporates both reflective and formative indicators and can handle high structural modelling complexities fairly easily. PLS offers great flexibility by providing very robust model estimations both with data that are normal (skewed or not) and non-normal (Reinartz *et al*., 2009; Ringle *et al*., 2009). Unlike covariance-based SEM (CB-SEM), PLS focuses on maximizing the endogenous latent variables' explained variance rather than reproducing the theoretical covariance matrix. When CB-SEM premises are violated or if the research objective is simply prediction rather than comparing competing theories, variance-based PLS is favoured (Reinartz *et al*., 2009; Ringle *et al*., 2009; Hair *et al*., 2011a).

Amongst some of the limitations of PLS we have the following: (1) structural model should be recursive, (2) no loops in the structural model are allowed, (3) the use of categorical data to measure endogenous latent variables is restricted, (4) it is prone to measurement model overestimation or structural relationships underestimates, and (5) only when the number of observations and indicators per construct increase do the construct case values approach their true values and the PLS bias disappears (Lohmöller, 1989). The basic PLS algorithm (Wold, 1975) and later extended by Lohmöller (1989) follows a two-stage approach, as cited in Henseler & Ringle's (2012) study and is as follows:

Stage 1: Iterative estimation of the latent variable scores

Do loop

Step 1.1: Outer approximation of the latent variable scores

Step 1.2: Estimation of the inner weights

Step 1.3: Inner approximation of the latent variable scores

Step 1.4: Estimation of the outer weights

Until convergence

Stage 2: Final estimation of the outer weights/loadings and path coefficients through (single and multiple) ordinary least squares regression.

In the only available PLS study by Ghulami, Hamid, and Zakaria (2014), the hypothesised model was assessed using the PLS methodology that linked all the constructs of attitudes of students with the perceived achievement. The study's aim was to investigate the relationship of attitudes of students towards learning statistics using several constructs which are: affect cognitive competence, value, difficulty, interest, effort and perceived achievement in statistics subject. The results reveal that all the relationships in the hypothesized model were significant at $p < 0.05$, and this suggests that all constructs of attitudes of students play a vital role in learning statistics. The impact of difficulty on cognitive competence has been found to be moderate and statistically significant and positive in the structural model (Onwuegbuzie, 2003; Sorge & Schau, 2003; Nasser, 2004; Budé *et al*., 2007; Tempelaar, Van der Loeff & Gijselaers, 2007; Emmoglu 2011).

Structural equation modeling was applied, and it is noted that the cognitive competence was highly correlated with affect in the model, as has been found in previous research that the relationship between the cognitive competence and affect is also highly correlated (Sorge & Schau 2002; Emmoglu 2011). This means that cognitive competence and affect are closely linked to each other. The relationship between the constructs of affect and interest is positive and statistically significant and the findings are in line with Emmoglu (2011) and Tempelaar *et al.* (2007). Similarly, the impact of difficulty and cognitive competence on interest are found to be statistically significant and positive.

The results also indicate that the relationship of interest on effort, value and statistics achievement are statistically significant. These findings are also supported by other studies such as Emmioglu (2011) and Emmioglu *et al.* (2012). However, there are mixed findings from previous studies on the relationship between value and statistics achievement (Sorge, 2001). It is noted that value had an indirect impact on statistics achievement (Nasser, 2004). The "attitudes of students' achievement towards statistics model" used in this study, however, confirmed the existence of a positive relationship between value and statistics achievement. The results showed that the effort is significantly correlated with the statistics achievement.

This technique had included confirmatory tetrad analysis (CTA) (Gudergan *et al*., 2008) that allows distinguishing between formative and reflective path or measurement models. In principle, the analysis follows Bollen and Ting's (2000) confirmatory approach and the Heterotrait-Monotrait (HTMT) criterion by Henseler, Ringle and Sarstedt (2015) shows by means of a simulation study that the classical approaches, that is the Fornell-Larcker criterion and cross-loadings, do not reliably detect a lack of discriminant validity of constructs in common research situations. These authors therefore propose an alternative approach, which is based on the multitrait-multimethod matrix: the heterotrait-monotrait ratio of correlations (HTMT) to test discriminant validity. These two were concomitant in the development of SmartPLS 3.0 statistical program (Ringle, Wende & Becker, 2015).

Other criteria and analysis procedure in the SmartPLS 3.0 include, but are not limited to consistent partial least squares (PLSc), importance-performance matrix analysis (IPMA), multigroup analysis (MGA), non-linear relationships, hierarchical component models, finite mixture (FIMIX) segmentation, prediction-oriented segmentation (POS), and others. These properties make SmartPLS 3.0 more preferred in the prediction stage of this study than AMOS 23.

2.4.1 Relevance of Partial Least Square Modeling

Due to the change in attitude of students throughout an academic year it becomes very difficult to measure their perception and attitudes or find factors that impact negatively on their academic achievement of the statistics subject. The misidentification of SEM models gives way for this correction or remedy by applying PLS to the sample data. The properties of PLS such as confirmatory tetrad analysis (CTA) (Bollen & Ting, 1993), hetero-trait monotrait (HTMT) (Henseler, Ringle and Sarstedt, 2015) and consistent partial least squares (PLSc) (Dijkstra & Henseler, 2015) are useful in this regard.

2.4.2 Variables in Partial Least Squares Modeling

From its origin, one can easily extrapolate which data are used in PLS analysis. As it originated in the social sciences, specifically economics (Wold, 1966) and became popular first in computational chemistry (see for example Geladi & Kowalski, 1986) and in sensory evaluation (Martens & Naes, 1989), it is not difficult to see that PLS algorithms can be used with either a continuous or discrete set of data.

2.4.3 Partial Least Squares Application

As mentioned earlier partial least squares application to students' perceptions and attitudes using the SAOM is minimal or virtually absent in the vast body of students' attitudes research. Therefore, this study attempts to use it to correct any possible problems that may be encountered due to model specification violations or model estimation errors. It is used primarily as an exploratory tool when at first CFA-SEM fails.

2.5 Chapter summary

This chapter has outlined the basis and congruence of the Statistics Attitudes-Outcomes Model and the Eccles' Expectancy-Value Model framework. The chapter further looked into similarities between the instruments adopted by this study (SATS-36 and MPSP) and the

Eccles’ Expectancy-Value Model. Moreover, this chapter reviewed studies on students’ perception and attitudes on statistics, specifically those that have used the structural equation modeling and partial least squares approaches as an analysis technique. The aim was to review those studies which have utilised SEM approach and managed to establish moderating, mediating, and causal effects from the structural model. There seemed to be a gap in this regard (few or no studies established that or used partial least squares analysis), which had formed the basis of this study. It has been found that very few of these studies have also determined discriminatory and nomological validity simultaneously, an attribute of the partial least squares algorithm.

This form of construct validity that requires a comparison of at least two constructs and that those constructs have a possible linkage. Both of these events occur, and appear to be correlated without being directly related to one another. Furthermore, this chapter made an attempt to provide evidence or lack thereof of the use of structural equation modeling and partial least squares approaches in studying students’ perception and attitudes on statistics subject, respectively. It provided the reader with evidence why the study adopted a variance-based approach (PLS-SEM) as a remedial method, if SEM fails to produce desired results. It has provided evidence for the use of SmartPLS 3.0 to do the statistical analysis and present results as it has a flexible PLS algorithm built in, as well as consistent PLS method, CTA and HTMT criteria, and an easy way to use an interface. The inclusion of more recent criteria in the statistical programme makes it a very flexible computer tool.

The method was chosen for its flexibility to deal with multivariate assumptions and the ability of the statistical software to estimate all coefficients, score, weights, check validity of constructs, the direction of indicator arrows and statistical tests (inferences) at a click of a button. Multivariate assumptions for structural equation modeling and partial least squares methodologies are discussed in-depth in chapter 3 and this includes the steps in the algorithm to attain the model with better fit than the rest.

Chapter 3

Research methodology

3.1 Introduction

This chapter provides an overview of the research design and methodologies employed in this study. The chapter focuses primarily on the setting of the research, subjects, and survey instruments utilised. Furthermore, the chapter describes and justifies the data-collection method used, the study design chosen, allocation conditions of the sample, investigated concepts and constructs, the sampling technique (population, sample selection and planned sample size), recruitment of subjects, the way of consent, etc. The chapter also describes and justifies the methods of data processing and analysis used. This study is a based on recommendations made by Ncube and Moroke's (2015) study. Different methodologies have different and specific multivariate assumptions, and some are more relaxed, to these multivariate assumptions demands, than others. Structural equation modeling (SEM) and partial least squares (PLS) employ different algorithms to analyse multivariate data.

SEM is restricted to uncovering and testing hypotheses of complex relationships between manifest and latent variables, whilst PLS is used to reveal underlying relationships and prediction. It will, where the methods measure the same thing, compare the outcomes. The process as summarised in Figure 3.1 will be followed when performing data analysis and the proposed methods are discussed here. Multivariate assumptions, as part of the research design, are also looked into and discussed briefly.

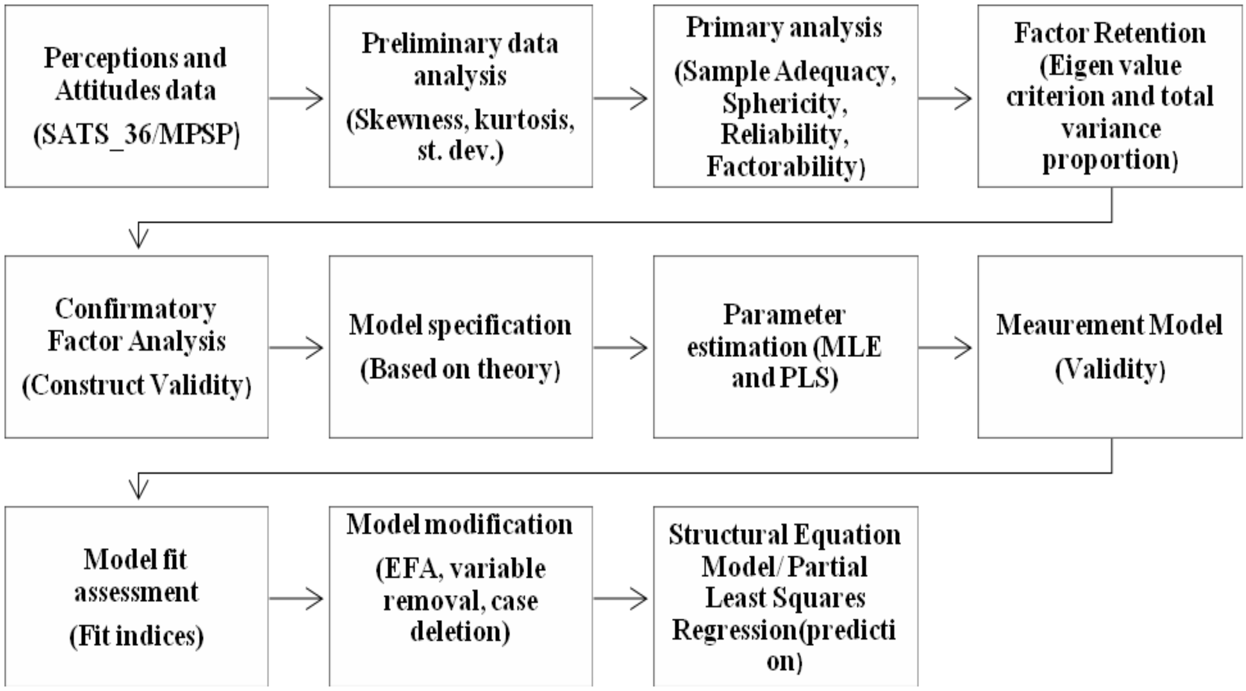

Figure 3.1: Structural equation modeling stages (adapted from Hair *et al*., 2010)

The rest of the chapter is structured as follows: firstly, Section 3.2 discusses data description and sources. Preliminary data screening is discussed in section 3.3. Primary data analysis is highlighted in Section 3.4. SEM and PLS algorithms are discussed in section 3.5 and 3.6, respectively. Section 3.7 gives the chapter summary.

3.2 Data description and source

Data were collected using the altered SATS-36 and MPSP self-administered questionnaires (using a Likert scale) from a first-year undergraduate class who availed themselves for statistics lectures. A proportionate stratified random sampling method was used to select respondents from a population of about 1000 students during the 2015 academic year at the Mafikeng Campus of the North-West University, South Africa. The respondents were randomly selected from their respective classes, which form strata and should have taken at least one introductory statistics course prior to the completion of the questionnaire. A random sample was selected within each group, to make up the final population sample of statistics students who availed themselves for lectures on a particular day. The population is divided according to groups of major courses.

The instrument was chosen due to the fact that it had recently been used to assess students' perceptions, attitudes and achievements towards statistics (Emmioglu, 2011). The psychometric properties of SATS-36 are well documented (Chiesi & Primi, 2009). The subscales are based on Eccles (1983) and Eccles & Wigfield's (1995) expectancy value model and Sorge & Schau's (2002) statistics attitudes-achievement structural model. As discussed in the first chapter, the hypothesised model consists of eight latent constructs, as opposed to seven in the previous studies. The first construct consisting of six items Af1 – Af9, is Affect which represents the students' positive and negative feeling towards the statistics subject. Cognitive competence (seven items CC1 – CC6); is the second construct which represents the students' perception about their intellectual knowledge and skills (Schau & Emmoglu 2011). Interest of statistics (five items I1 - I5); is the third construct which assesses students' level of their individual interest in statistics subject (Schau & Emmoglu, 2011).

Value construct (where nine items V1 - V9 were coded); is the fourth construct that assesses students' perceptions and attitudes towards the advantage, worth, relevance and usefulness of statistics for an individual and for individuals in their careers (Schau & Emmoglu, 2011). Effort (where four items E1-E4 were coded); is the fifth construct which seeks to measure the time expended by the students in learning statistics (Schau&Emmoglu 2011). The statistics self-efficacy construct (where six items SE1- SE6 were coded) assesses the students' perceptions and confidence about their individual use of statistics (Sorge & Schau 2002).

Difficulty (where seven items D1-D7 were coded) is an exogenous construct which aims to measure the attitudes of students towards the inabilities or difficulties in understanding statistical computations or concepts (Schau & Emmoglu 2011). The statistics outcomes construct (where three items SO1-SO3 were coded); assesses the students' perception on the application of statistics in solving real-life problems and refers to the students' achievement in learning, understanding and applying (Cherny, 2005). Lastly, three more items were included, two into the Affect construct and one in the Interest construct. All these items' statements and sub-scales mentioned above are shown in Table 3.1. Structural Equation Modeling is employed in the analysis of the data using IBM SPSS 22, SAS 9.3 and smartPLS 3.0. The technique helps to determine constructs, relationships between these constructs, components that form them and possible prediction model. The methodology and sample requirements are discussed further in Chapter 3 of this study.

The use of categorical data satisfies one of the necessary conditions for confirmatory analysis as cited in O'Rourke *et al.* (2013) namely, the use of normal and categorical data. Other necessary conditions are discussed under model specification and assumptions. The questionnaire was handed to students as they walked into lecture halls. Instructions on how to respond to the questions were clearly stated on the questionnaire. To select the sample for this study, a proportionate stratified probability sampling method was used to select participants to form the sample. The different classes formed strata of the sample.

If sampling is found to be appropriate for a particular research project, the researcher then identifies the target population in relation to the purpose of study, selects the sample, and decides on an apt sampling method to estimate population parameter. Using the proportionate stratified random sampling design, the sample distribution of this study is structured according to Table 3.1.

Table 3.1: Proportionate samples

Stratum	Population of stratum	Proportion aimed	Sample size	% of final sample
1	542	0.7	251	43.05%
2	177	0.5	165	28.30%
3	143	0.5	85	14.58%
4	91	0.5	82	14.07%
Total	953		583	100%

Stratified sampling is defined as a probability sampling technique which the researcher uses to divide the population into homogenous subgroups called strata, according to (Cochran, 1953). Of importance, is to make sure that membership among strata is non-overlapping. The sample size for the present study is 583 subjects, which is in agreement with Hair *et al.* (2010) sample size requirements and fulfils the minimum sample and ratio of subjects per variable requirements (Kline, 2011).

3.3 Preliminary data analysis

Preliminary analysis of data suggests to the researcher which suspect cases or variables to be removed or revised as per objectives of the study. Preceding sections deal with methods followed to clean the data without compromising sample size or quality. These include: missing data, multicollinearity, normality, sample adequacy and factorability. Primary data analysis for both methodologies, which also involves model modification, follows the preliminary data-analysis process.

3.3.1 Data screening: Case and variable screening

It happens before the actual data analysis to deal with troublesome cases or variables. The most common problems encountered in self-administered questionnaire surveys are missing data, unengaged responses from participants, severely leptokurtic or platokurtic data sets, according to Gaskin (2012). Gaskin (*ibid.*) suggests looking at standard deviations and data counts, case-wise, to determine suspect respondents in input data. To determine the missing data, Gaskin (*ibid.*) suggests using frequencies and data imputation if necessary.

The statistical packages SPSS 22, Microsoft Excel 2013 and SAS 9.3 were used to determine cases or variables of concern to the researcher. As outlined in Mueller (1997), SEM involves a series of steps to be followed in order to attain the structural equation. These include: (a) initial model specification, (b), parameter identification and estimation (c) data-model fit assessment, and (d) model modification.

3.3.2 Sample size

The SEM procedure is based on large sample theory (Lehmann, 1999), and minimum sample requirement is asserted to reliably conduct an SEM study. Some authors recommend a sample of minimum 200 observations for CFA, while others say a threshold of 300 is more appropriate. According to Hair *et al*. (2010), sample sizes of 50 observations suffices under ideal conditions using maximum likelihood estimation (MLE), but recommend a sample size of 200 to provide a sound basis for estimation. Hair *et al.* (2010) suggest the following rules of thumb based on model complexity and basic measurement model characteristics: (a) $\leq$ 100 observations; when model has not more than five constructs, and high item communalities ($\geq$ 0.6), (b) $\leq$ 150 observations; when a model has constructs not exceeding seven, and no under-identified constructs with modest communalities ($\approx$ 0.5), (c) when a model has low communalities ($\leq$0.45), (d) multiple under-identified constructs and not more than seven constructs, then a minimum sample of 300 is recommended, (e) a minimum sample of 500 is suitable for models with a large number of constructs, with lower communalities or having under-identified constructs.

The study sample is 583 and conforms to these aforementioned requirements. The general rule of thumb suggests at least 300 cases for factor analysis. "Solutions that have several high loading marker variables (> .80) do not require such large sample sizes (about 150 cases should be sufficient) as solutions with lower loadings" (Tabachnick & Fidell, 2007:613). Bryant & Yarnold, 1995:100) state that, "…one's sample should be at least five times the number of variables. The subjects-to-variables ratio should be 5 or greater. Analysis should be based on a minimum of 100 observations…" Researchers vary in their elucidations, in terms of the number of cases required to conduct factor analysis. Ratios of 5:1 (about 200 cases) and 2:1 (about 100 cases) respectively of subjects to variable are proposed by Kline (2011). Hutcheson & Sofroniou (1999) recommend 150 to 300 cases on the other hand. The sample acquired meets all the sample requirements suggested by these studies.

Hinkin (2009), as cited in Montshiwa and Moroke (2014) emphasises the use of large samples in factor analysis to assist in obtaining stable standard errors. This also ensures that factor loadings reflect the population accurately. A common rule of thumb is to have a minimum of 10and maximum of 15cases per variable. Comrey and Lee (1992) propose the following criteria; 50 = very poor, 100 = poor, 200 = fair, 300 = good, 500 = very good and >1000 = excellent. Hair *et al.* (2010) criterion (e) was employed in determining the sample size for this study. This is also in line with Comrey and Lee's (1992) criterion. The sample size and resulting degrees of freedom for the current study should be such that they provide sufficient statistical power, that is, assuming a medium to large effect size and a standard threshold at $\alpha = .05$ level of significance (MacCallum, Browne, & Sugawara, 1996) and (MacCallum *et al*., 2001).

3.3.3 Reliability and sphericity

To determine if the sample is appropriate for factor analysis, Bartlett's test of sphericity is used (Bartlett, 1954). Pett *et al*. (2003) recommended the following criteria in deciding adequacy: less than 0.50 is unacceptable, at least 0.50 but less than 0.60 is miserable, in the range of 0.6s is mediocre, at least 0.70 to less than 0.80 is middle, 0.80s is meritorious and ≥ 0.90 is marvellous sampling adequacy (Kaiser, 1974). The following formula is used as a description of the KMO test;

$$MSA = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} q_{ij}^2}, \qquad (3.12)$$

where r_{ij}^2 is the square of the element from$R$, the correlation matrix, and q_{ij}^2 is the square of an element from $Q = DR^{-1}D,$ with $D = [(diagR^{-1})^{\frac{1}{2}}]]^{-1}$. As R approaches a diagonal matrix, the measure of sample adequacy (MSA) approaches 1.00. Cronbach alpha measures the inter-correlation or internal consistency of items of the instrument. The criteria suggest that Cronbach's alpha is significant when 0.7 ≤ α ≤ 0.8. Cronbach & Shavelson (2004) use the following rules of thumb: α ≥ 0.9 is excellent, 0.8 ≤ α < 0.9 is good, 0.7 ≤ α < 0.8 is acceptable, 0.6 ≤ α < 0.7 is questionable, 0.5 ≤ α < 0.6 is poor and α < 0.5 as unacceptable, as a rule of thumb Nunnally (1978) suggested 0.7 or more as acceptable.

Kaiser-Meyer-Olkin (KMO) statistics confirms sample sufficiency, as cited from Pett *et al.* *(*2003).As highlighted by Field (2013) it tells if the sample size is large enough to extract reliable factors. Pett *et al*. (2003) recommended the following criteria to decide on the adequateness; less than 0.60 is mediocre, miserable or unacceptable, in the 0.70 is middle, in the 0.80s is meritorious and above the 0.90 is marvellous. Kurtosis, skewness and normality plots were also considered in their study in measuring normality. This study will look at individual variable kurtosis, skewness and normality plots to measure univariate normality.

3.3.4 Singularity and factorability

The absence of multicollinearity is another necessary condition for CFA. If the determinant of correlation matrix and eigenvalues associated with some factors approaches 0, multicollinearity or singularity may be present. If there are correlations,$r \geq 0.8$, between any two variables, multicollinearity may be a problem (O'Rourke & Hatcher, 2013). Tolerance values are expected to be high, as closer to 1.0 as possible for all or most of the variables. Squared multiple correlations (SMCs) of a variable which serves as DV with the rest as IVs in multiple correlation (Tabachnick & Fidell, 2007) were explored. SMCs should be low, approaching to 0.00. If any of the SMCs are one (1), then there is singularity. Very large (i.e., near one), SMCs mean that multicollinearity is present (Tabachnick & Fidell, 2007).

If the VIFs (or tolerances), correlations or SMCs do not meet the criteria mentioned herein, then the suspect variables will be noted and not removed prematurely. Rule of thumb provides that if any of the VIF values exceeds 5 or 10, it implies that the associated regression coefficients are poorly estimated because of multicollinearity (Montgomery, 2001). Condition Index for each item is examined next and according to Tabachnick & Fidell

(2007) condition Index values should be greater than 30. Tabachnick & Fidell (2007), suggest that two variance proportions should not be greater than 0.50 for each item. Generally, high condition indices, variance proportions values and intercorrelations among independent variables above 0.80 signal a possible presence of multicollinearity. The criterion used for this research is VIF values, as relying only on one of the criteria is not ideal.

3.3.5 Multivariate Assumptions (SEM)

Structural equation modeling has its foundations deeply rooted in the classical path analysis (Wright, 1918) and CFA (Jöreskog, 1966). This text follows a two-step approach first described by Anderson and Gerbing (1988) and later Andersen & Gerbing (1992) and highlighted also by Chin (1998), for performing analysis of covariance structures. The initial step involves developing an acceptable measurement model using *confirmatory factor analysis* (CFA), based on theory and a priori specified causal hypotheses (Mueller & Hancock, 2008). This suggests that SEM is inherently a confirmatory technique. Finally, computing a structural model is based on theoretically conceptualised underlying *causal* or *path model*. Maximum likelihood estimation (MLE) method is widely used, and assumes underlying *multivariate normality*.

CFA and SEM assumptions would apply and adhered to in developing the measurement models and later the structural model. These assumptions include multicollinearity, indicator and latent construct reliability, sphericity, sample size, and the singularity or factorability of the correlation matrix. These methods are further used when responding to the research questions and hypotheses set by the study in Chapter 1. In SEM, a multivariate normal distribution determines what parameter estimation method the researcher would use, and to what extent the parameter estimates are trustworthy.

3.3.5.1 Tests for normality

The Mardia's skewness and kurtosis tests

The skewness and kurtosis have long been used in detecting non-normality of univariate data (Pearson, 1930). Non-normality, can produce poor estimates and grossly inaccurate standard errors and hypothesis test results. Consequently, the assumption of normality is much more important than in models with non-stochastic exogenous variables. For multivariate normality, Mardia (1970) developed two statistics for measuring multivariate skewness and kurtosis. The skewness statistic Mardia's measure of multivariate skewness (MS) is:

$$MS = \frac{1}{6n}\sum_{i,j=1}^{n}(Y_i^T Y_j)^3, \tag{3.1}$$

where n is the sample size, **Y** is the matrix of random variable of interest. The kurtosis statistic Mardia's measure of multivariate kurtosis MK is:

$$MK = \sqrt{\frac{n}{8p(p+2)}}\left\{\frac{1}{n}\sum_{i=1}^{n}\| Y_i \|^4 - \frac{p(p+2)(n-1)}{n+1}\right\}, \tag{3.2}$$

where n is the sample size, p is the number of parameter to be estimated, and Y_i is the observed data.

The skewness test rejects the null hypothesis of normality, if MS is too large, and the test based on the centralized kurtosis statistic MK rejects the null hypothesis of normality if its absolute value |MK| is too large, that is, the p-value of the test exceeds the critical value (Shao & Zhou, 2014). As an alternative way, Bowman and Shenton (1975) considered combining skewness and kurtosis equivalent to the following statistic:

$$MSK = MS + \|MK\|^2 \tag{3.3}$$

which has an asymptotic distribution in the univariate case. Doornik & Hansen (2008), in the multivariate case, demonstrated some practical utility and good power performance of MSK. This statistic is available in SAS 9.3 as a default multivariate normality checker. In fact, Mardia's test of multivariate kurtosis has been shown to have good properties for detecting multivariate outliers in some situations (Schwager & Margolin, 1982). The relation of Mardia's (1970) measure to the Mahalanobis distances is also helpful for understanding the measure: A large value of Mardia's measure, relative to the expected value under multivariate normality, suggests the presence of one or more cases with large Mahalanobis distances. These are cases that are far from the centroid of all cases (potential outliers), suggests (DeCarlo, 1997). Mardia's multivariate kurtosis in part indicates if the tails are heavy or light relative to those of the multivariate normal distribution. If it's difficult to obtain multivariate normality after deletion of cases, then the study would opt for Shapiro-Wilks normality test (Shapiro & Wilk, 1965).

The Shapiro-Wilk test

The SW test statistic is regarded as the ratio of two variance estimators, the best linear unbiased estimator (BLUE) and the maximum likelihood estimator (MLE) as cited in Shao and Zhou (2014). The Shapiro-Wilk (SW) test, which was originally developed for testing univariate normality, has the following form:

$$W_n(z_1,..., z_n) = \frac{\left\{\sum_{i=1}^{n} a_{n,i} z_{(i)}\right\}^2}{\sum_{i}^{n}\left(z_i,..., \bar{z}_n\right)^2}, \tag{3.4}$$

where $z_1,\ldots,z_n$ is the observed univariate data, $z(1), \ldots, z(n)$ are order statistics of $z1, \ldots, zn$, $\bar{z}_n$ is the sample mean of the univariate variable, and the constants $a_{n,i}$ are $\left(a_{n,1},..., a_{n,n}\right) = \left(m^T V^{-1} V^{-1} m\right)^{-1/2} m^T V^{-1}$, with $m = \left(m_1,..., m_n\right)^T$ and V the mean covariance of the order statistics of a random standard normal sample of size n, respectively. Browne's (1984) asymptotically distribution-free (ADF) estimation method may be used, if the number of observations is sufficiently large. The study uses Shapiro-Wilk test, using the SAS 9.3 PROC UNIVARIATE, to determine univariate skewness. Furthermore, this study uses the following Mardia's statistics from the SAS 9.3 PRO CALIS to determine multivariate kurtosis of the data:

(1) Mardia's multivariate kurtosis can alternatively be written as:

$$\gamma_2 = \frac{1}{N}\sum_{i}^{N}[(z_i - \bar{z})' S^{-1}(z_i - \bar{z})]^2 - p(p+2), \tag{3.5}$$

Where **S** is the biased sample covariance matrix with N as the divisor. In the following equations, N denotes the sample size and p is the number of variables.

(2) Relative multivariate kurtosis, given by:

$$\eta = \frac{\gamma_2 + p(p+2)}{p(p+2)}, \tag{3.6}$$

(3) Normalized multivariate kurtosis:

$$\kappa_0 = \frac{\gamma_2}{\sqrt{8p(p+2)/N}}, \tag{3.7}$$

(4) Mardia based kappa (Browne, 1982):

$$\kappa_1 = \frac{\gamma_2}{p(p+2)}, \tag{3.8}$$

(5) Mean scaled univariate kurtosis:

$$\kappa_2 = \frac{1}{3p}\sum_j^p \gamma_{2(j)}, \tag{3.9}$$

and (6) Adjusted mean scaled univariate kurtosis:

$$\kappa_3 = \frac{1}{3p}\sum_j^p \gamma^*_{2(j)}. \tag{3.10}$$

If variable Z_j is normally distributed, the uncorrected univariate kurtosis $\gamma_{2(j)}$ is equal to 0. If Z has a p-variate normal distribution, Mardia's multivariate kurtosis γ_2 is equal to 0. The values of κ_1, κ_2, and $\kappa_3$should not be smaller than the following lower bound (Bentler, 1985):

$$\hat{\kappa} \geq \frac{-2}{P+2} \tag{3.11}$$

PROC CALIS displays a message if κ_1, κ_2, or κ_3 falls below the lower bound. The occurrence of significant nonzero values of Mardia's multivariate kurtosis γ_2 and significant amounts of some of the univariate kurtosis values $\gamma_{2(j)}$indicate that your variables are not multivariate normal distributed.

3.4 Primary data analysis

When all assumptions under CFA are met and all necessary SEM conditions are met, primary data analysis follows. PLS has more relaxed assumptions as alluded to in previous chapters. This section deals with CFA, SEM and PLS assumptions, rules of thumb, including their executable steps in their algorithms. These steps include hypothesized model, model specification, fit assessment and modification.

3.4.1 Confirmatory Factor Analysis

Factor Loadings

This method is a precursor to SEM. Factor loadings with a value ≥ |0.3| may be considered in order to continue with factor analysis, specifically when the sample size is 100 or larger, suggests (Hair *et al*., 2010). Tabachnick & Fidell (2007) used a loading of 0.45. Tabachnick and Fidell (*ibid.*) also recommend a minimum factor loading of 0.32. Comrey and Lee (1992) suggest that loadings in excess of 0.71 (50% overlapping variance) are considered excellent, 0.63(40% overlapping variance) are considered very good, 0.55(30% overlapping variance) are considered good, 0.45 (20% overlapping variance) are considered fair, and 0.32 (10% overlapping variance) are considered poor. Choice of the cut-off for size of loading to be interpreted, according to Tabachnick & Fidell (2007), is a matter of a researcher's preference. Next, the internal consistency of the items which have high factor loadings on each of the factors (i.e., > 0.40) is examined (Hair *et al.,* 2010).

Tabachnick & Fidell's criterion is followed to determine the number of factors to be retained. Since many of the statements are related or correlated cross-loadings are expected. As expected, each manifest variable should load more into the latent variable it is supposed to measure, according to Chin (1998), as cited in Gregoirè & Fisher (2006). Negative Cronbach alpha discrepancies could be due to selection or extraction of fewer factors accounting for minimal variance. This is the contravention of one of the suggested rules of thumb for determining how many factors should be retained, as suggested by Field (2009) and Rietveld and Van Hout (1993), to keep factors with total variance of 70 to 80%. The following table (Table 3.2) adapted from Hair *et al*. (2010:117) gives guidelines for identifying significant factor loadings based on a study's sample size. Significance is based on 0.05 significance level, power level of 80 percent, and standard errors assumed to be twice those of conventional correlation coefficients.

Table 3.2: Factor loadings based on sample size

Factor Loading	Sample size needed for significance
0.30	350
0.35	250
0.40	200
0.45	150
0.50	120
0.55	100
0.60	85
0.65	70
0.70	60
0.75	50

The common factor model is written as:

$$x = \Lambda_x \xi + \delta , \tag{3.12}$$

where **ξ** is a vector of latent variables via a vector or manifest variables, $x = (x_1, x_2 ..., x_q)'$. The matrix $\Lambda_x (q \times n)$ is the factor loading matrix. The common factors have zero mean $E(\xi) = \mathbf{0}$and the covariance matrix **Φ**. **δ** are vectors of unique factors of the elements of **x**, with $E(\delta) = \mathbf{0}$and$\boldsymbol{\Theta}\delta$is the covariance matrix of **δ**. It is assumed that $Cov(\delta, \xi) = \mathbf{0}$. Thus the covariance structure of **x** written as:

$$\Sigma = \mathrm{cov}(x) = \Lambda_x \Phi \Lambda_x' + \Theta_\delta , \tag{3.13}$$

3.5 Structural Equation Modeling framework

This section outlines the algorithm to be executed from the sample data to the final structural model. These steps give an account of the steps from model conceptualization to model identification, through to model modification and the final model. Jackson, Gillaspyan &

dPurc-Stephenson (2009) suggest that model modification should be done only when they are theoretically plausible and sparingly (e.g. McCallum, 1995).

3.5.1 Model specification

The model is based on relevant theoretical framework outlined under *theoretical framework* section (in Chapter 2) of this study. Related literature has been reviewed in Chapter 2 of this study. Variables and constructs from the SATS-36 and MPSP survey instruments, chosen as they are believed to respond to the set objectives of the study. An inclusion of nontrivial variables is a necessary condition of confirmatory factor analysis. The model is based on the hypotheses stated in Chapter 1 of this study, of which the variables are from a validated SATS-36 and MPSP questionnaires. The hypothesised models are represented schematically and in equation form based on the following general equations:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{3.14}$$

where $\eta = (\eta_1, \eta_2, ..., \eta_m)'$ are latent dependent variables and $\xi = (\xi_1, \xi_2, ..., \xi_n)'$ are latent explanatory variables. Note that B is a matrix of path coefficients relating the latent dependent variables to each other, Γ is a matrix of path coefficient relating latent dependents to latent explanatory variables and ζ is a vector of disturbances. It is assumed that $E(\xi) = 0, E(\zeta) = 0$ and $Cov(\xi, \zeta) = 0. Cov(\xi) = 0$ and also $Cov(\zeta) = 0$. Confirmatory factor or measurement models are specified for η as:

$$y = \Lambda_y \eta + \varepsilon, \tag{3.15}$$

where y is a continuous measure, Λy is the factor loading matrix and $\Theta\varepsilon$ is the covariance matrix of ε. It is assumed that $E(\varepsilon) = 0, Cov(\varepsilon, \eta) = 0, Cov(\varepsilon, \xi) = 0, Cov(\delta, \xi) = 0,$ and $Cov(\varepsilon, \zeta) = 0$ and $Cov(\varepsilon, \delta) = 0.$

The general forms of equations (3.12) through to (3.15) suggest that these estimated relationships are linear and additive. Yet another necessary condition for measurement model analysis. CFA will ensure as per SATS-36 (Schau, 2003) and later studies that each construct has three or more variables per construct (identified constructs). This is another necessary condition for confirmatory or measurement model analysis. The exception to this condition is mentioned in Hair *et al*. (2010), that is, an unidentified construct maybe be seen in analysis involving large samples with many constructs. This is highlighted in the sample size and adequacy testing section.

The following are some of the rules to be followed when specifying a structural model, as adapted from O'Rourke & Hatcher (2013, p258): Firstly, only covariances of exogenous variables can be estimated in the model (see Figure 3.4) in the next pages. Secondly, every endogenous variable can be identified with an error term. Thirdly, exogenous variables have no residual terms. Fourthly, variance should be estimated for every exogenous variable is the model, including error terms. Fifth rule: an equation for each endogenous should be created with that variable's name to the left of the equal sign. The sixth rule states that variables that have a direct effect on that endogenous variable are listed to the right of the equal sign.

The seventh rule holds that endogenous variables and error terms are never listed to the left of the equal sign (refer to Figure 3). The eighth rule suggests that the last term in each equation should be the error (disturbance) term for that endogenous variable; and it will have no name assigned to its path coefficient. Ninth rule states that, in CFA the variances of the constructs are fixed at 1, but in SEM the variables of the latent variables are free parameters that have to be estimated. The tenth rule says, in SEM, for each construct one factor loading should be fixed to 1. The eleventh rule suggests that more often than not, covariances for every pair of observed or endogenous variables; and not required for outcome variables. Rule twelve states that the covariances are not estimated for error terms, in simple recursive models (but relaxed in more elaborate models (O'Rourke *et al.,* 2013)).

The thirteenth rule says a unique path name should be created for every path of every independent variable. The fourteenth rule states that a value should be put in place of a parameter's name in order to fix it a certain numerical value. The fifteenth rule says that, in SEM, variances of outcome variables are free parameters, that is, they have to be estimated. Lastly, the same name should be used to constrain two or more parameters as equal. A measurement model is a relationship between indicator variables and latent variables. A structural model is a relationship between indicator variables via a first-order or second-order latent variable. The relationship between exogenous and endogenous variables is represented by Figures 3.2 to 3.4. The relationship between observable and unobservable variables, that is, the indicator and latent variables that form the measurement and structural model, respectively, is represented by Figure 3.5. It represents the matrix equation (3.14).

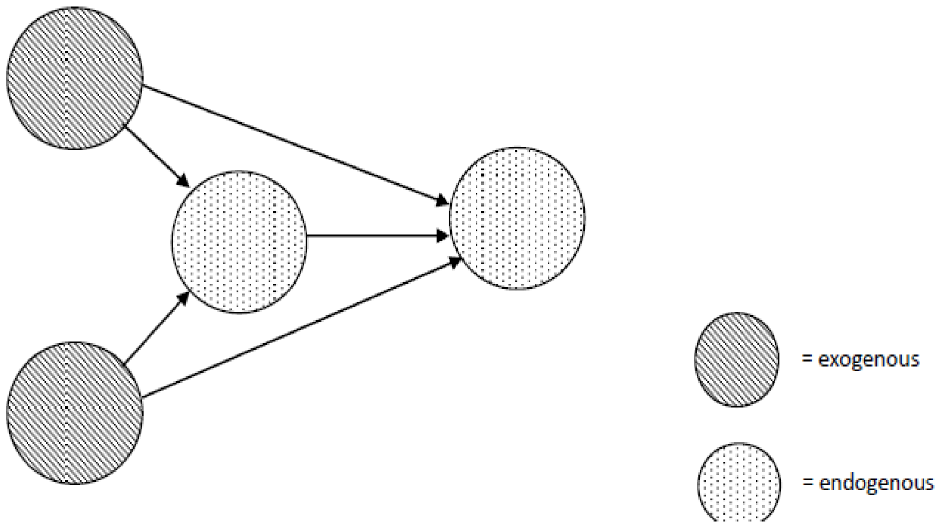

Figure 3.2: Exogenous and endogenous latent variables

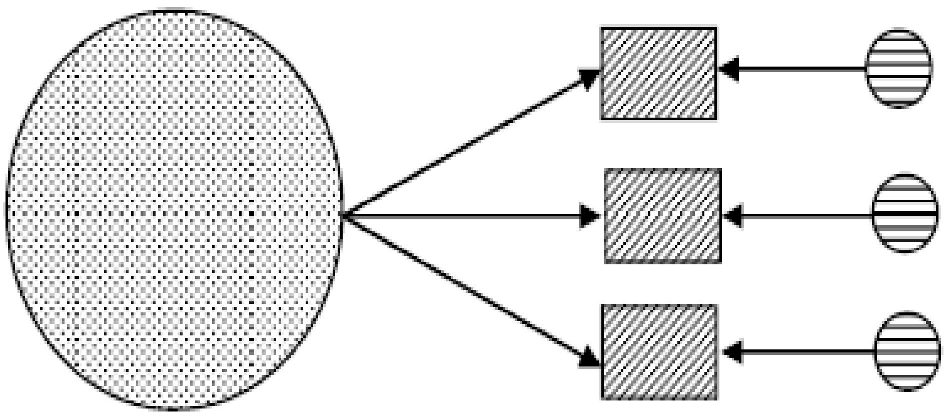

Figure 3.3: A formative construct (left), with indicators (centre) and error terms (right).

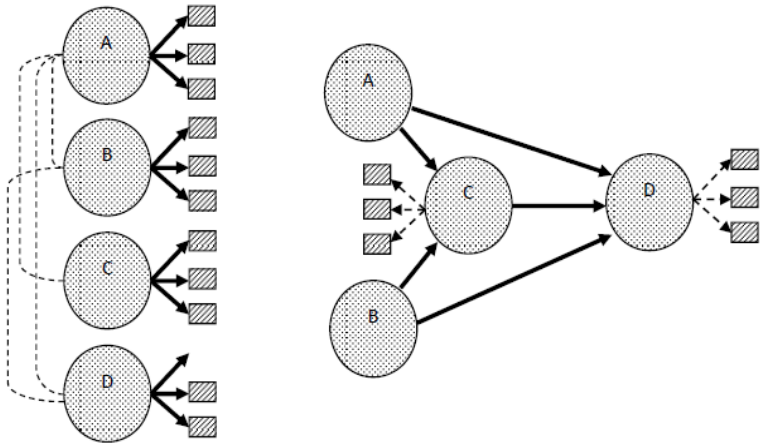

Figure 3.4: Constructs A, B, C, D: Measurement model with covariances (dotted lines) (left) and structural model (right).

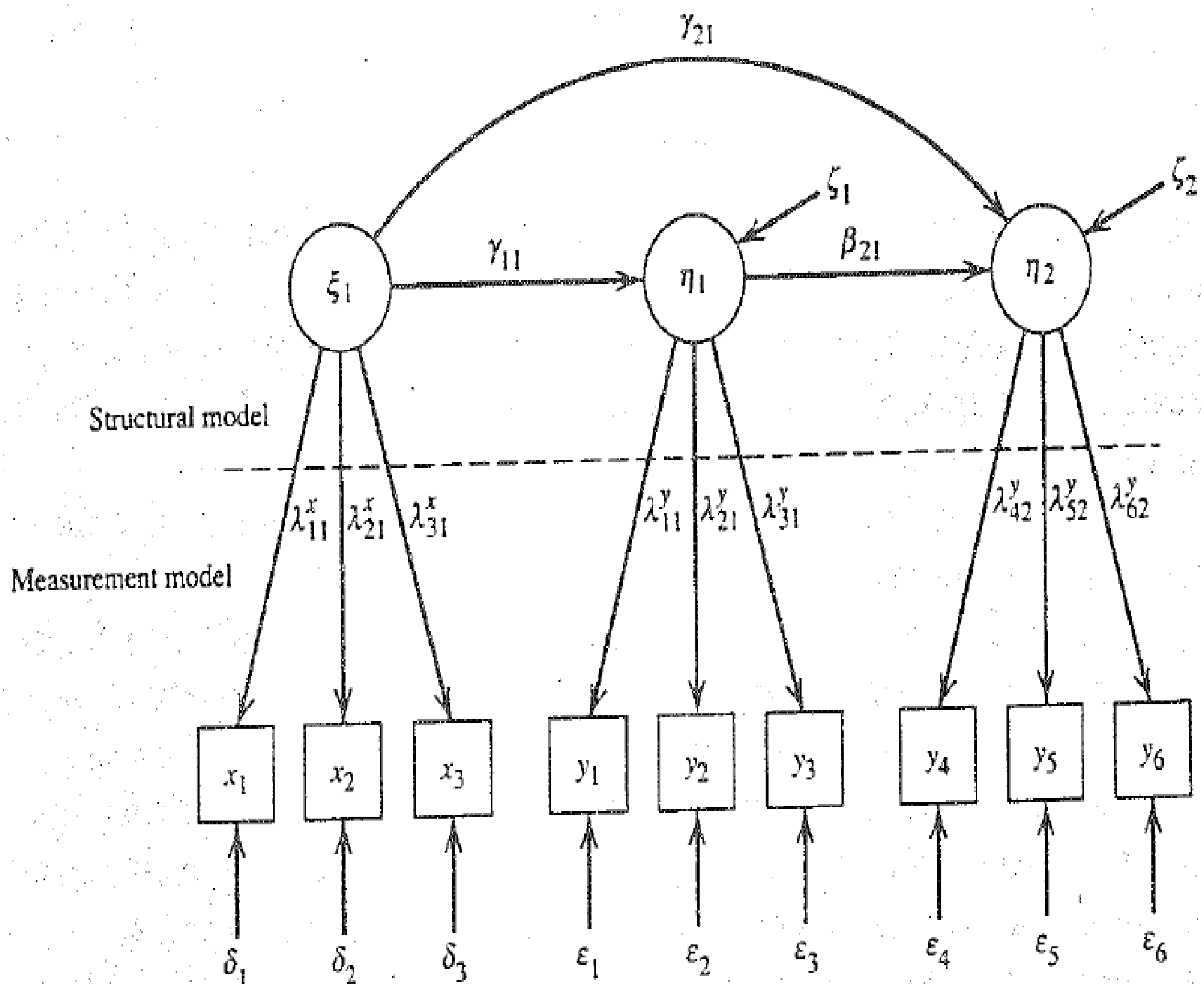

Figure 3.5: Structural model with latent constructs

The measurement model (matrix equation 3.12) is represented by the following equations:

$$x_1 = \lambda_{11}^{x}\xi_1 + \delta_1 ;\; x_2 = \lambda_{21}^{x}\xi_1 + \delta_2 ;\; x_2 = \lambda_{31}\xi_1 + \delta_3$$

$$y_1 = \lambda_{11}^{y}\eta_1 + \varepsilon_1 ;\; y_2 = \lambda_{21}^{y}\eta_1 + \varepsilon_2 ;\; y_3 = \lambda_{31}^{y}\eta_1 + \varepsilon_3$$

$$y_4 = \lambda_{42}^{y}\eta_1 + \varepsilon_4 ;\; y_5 = \lambda_{52}^{y}\eta_1 + \varepsilon_5 ;\; y_6 = \lambda_{62}^{y}\eta_1 + \varepsilon_6 \tag{3.16}$$

The hypotheses are represented by the following mathematical equations:

$$Cognitive\_Competence = \beta_0 + \beta_1 Difficulty + error \tag{3.17}$$

$$Affect = \beta_2 + \beta_3 Cognitive\_Competence + error \tag{3.18}$$

$$Interest = \beta_4 + \beta_5 Affect + \beta_6 Difficulty + \beta_7 Cognitive\_Competence \tag{3.19}$$

$$\text{Value} = \beta_8 + \beta_9\text{Interest} + \beta_{10}\text{Affect} + \text{error} \tag{3.20}$$

$$\text{Effort} = \beta_{11} + \beta_{12}\text{Cognitive\_Competence} + \beta_{13}\text{Interest} + \beta_{14}\text{Value} + \text{error} \tag{3.21}$$

$$\text{Self-Efficacy} = \beta_{15} + \beta_{16}\text{Interest} + \beta_{17}\text{Difficulty} + \beta_{18}\text{Effort} + \beta_{19}\text{Value} + \text{error} \tag{3.22}$$

$$\text{Statistics Outcome} = \beta_{20} + \beta_{21}\text{Self\_Efficacy} + \beta_{22}\text{Value} + \beta_{23}\text{Affect} + \beta_{24}\text{Cognitive\_Competence} + B_{25}\text{Effort} + \text{error} \tag{3.23}$$

3.5.2 Model identification

A topic believed to be most often confusing and difficult in SEM is identification. According to (Suhr, 2006), a model is said to be identified if there exist numerical solutions for every parameter in the model. Estimation is only possible with identified models. A hypothesized model where it is possible to express parameters as functions of variances and covariances of the observed or manifest variables, is said to be *identified.* To attain a solution, the number of known parameters in the sample covariance matrix must be greater than or equal to the number of free parameters q. This is denoted as:

$$p^* = \frac{p(p+1)}{2}, \tag{3.24}$$

where p is the number of measured variables as per sample covariance matrix $(q \leq p*)$. A model is *just-identified* if $q = p*$, that is, a parameter can be estimated through only a single manipulation of the data. If the number of estimated parameters is greater than the unique variances and covariances, where $q > p*$, the model is *under-identified*. This implies, one or more unique estimations of free parameters are possible from the data. When a model is over-identified, $q < p^*$, it implies that free parameters can be estimated in multiple ways from the sample data.

3.5.3 Parameter estimation

The sole aim of parameter estimation is to obtain numerical values for free (unknown) parameters through an estimation technique, as discussed in (Bollen, 1989) for a technical approach, and Ullman (2006) for an applied viewpoint. In SEM, MLE is widely used. Alternative techniques are available, owing to sample distributional properties or available as per statistical package: (a) robust estimators (Bentler, 1994), asymptotically distribution free (ADF) (Browne, 1984), and generalised least squares (GLS). The MLE method is adopted in this study as the estimates are approximate in value to the population parameters and robust. The discrepancy function criterion for parameter estimation aims to optimise the difference between the population as estimated sample covariance estimates and the covariance matrix derived from the hypothesised model. The discrepancy function as in (Jöreskog, 1967) is given by:

$$Fml = log|\boldsymbol{\Sigma}(\mathbf{0})| + Trace[\boldsymbol{\Sigma}(\mathbf{0})] - log\,|\boldsymbol{S}| - \boldsymbol{p}, \tag{3.25}$$

where$\boldsymbol{\Sigma}$ is the population covariance matrix, $\boldsymbol{S}$ is the sample covariance matrix, and $\boldsymbol{\Sigma}(\mathbf{0})$is the covariance matrix due to the hypothesised model. Fixed parameter values are not estimated from data, and have values of either zero or one. The error variance of each latent variable and the parameter value associated with one of the paths from the latent variable to the indicator variable should be fixed at 1.0, suggests (O'rourke, Cappeliez, & Guindon, 2003). The disturbance is on the endogenous latent variable. According to Suhr (*ibid.*), the significance of the variable is set the 0.05 significance level, and the value should exceed $t \geq 1.96$ or 0.10 level of significance if $t \geq 2.56$. Effect size or weight is the value of the path coefficient. Standardised coefficients ≤ 0.10 may indicate a small effect, values ± 0.30 a medium effect, and ≥ 0.50 a large effect.

3.5.4 Measurement Model Validity

Measurement phase

The first stage of SEM is CFA, where a measurement model is estimated through the parameter estimation model and evaluated via the Cronbach's alpha threshold of $\alpha \geq 0.70$ as explained under the *reliability and adequacy of the sample* section. This includes *convergence and construct, discriminant and nomological validity.* The Fornell & Larcker (1981) criterion of average variance extracted (AVE) is also a measure for convergence validity. As cited in Groenland & Stalpers (2012), AVE of 0.50 or higher for latent endogenous variables are accepted. AVE > 0.50 and Cronbach's alpha ≥ 0.70 will be employed by the study to assess convergent reliability. Discriminant validity is defined as the extent to which constructs are distinct from one another (Hair *et al.*, 2006). This is assessed through inter-factor correlations. Nomological validity is the degree to which a construct correlates or covariances with other construct with the structural model (Bagozzi, 1980). It is established when the correlations or covariances within the structural model makes contextual sense (Hair *et al.*, 2006). This kind of validity can be demonstrated through the basis of the theoretical framework of the study. Construct correlations and covariances will be used to assess and establish nomological validity.

3.5.5 Model fit assessment

There are a number of indices developed over the last century to assess model fit, that is, how well does the hypothesised model fit the data. There are generally three classes: (a) absolute fit indices measure overall goodness-of-fit, (b) comparative fit indices measure the fit of the model comparing it to the baseline or null model, and (c) parsimonious fit indices measure level of parsimony in the estimated models. Goodness of prediction is assessed by comparing the actual values of the endogenous variables with their predicted values, usually in terms of root mean squared error or proportion of variance accounted for (R^2) (O'Rourke, Psych & Hatcher, 2013). For latent endogenous variables, root mean squared error and R^2 can be estimated from the fitted model. The critical ratio of path estimates is when t-value > 1.96

(Hair *et al.*, 2006; Byrne, 2001) and the recommended value for standard residuals is ± 2.8 (Hair *et al.*, 2006; Byrne, 2001).

The model fit indices that are widely used are presented in Table 3.3. The other tests that are taken into account are the Wald and Lagrange Multiplier (LM) tests. Table 3.4 adapted from Hair *et al.* (2010:672) shows the goodness-of-fit across different model situations. These were based on simulation research that considers model complexity, degrees of error in model specification for different sample sizes (Marsh *et al*., 2004).

Table 3.4: Model Fit Indices

Category	Index name	Level of acceptance	Literature
Factor Loading	Standardized Regression Weight	weight 0.6	Hair *et al.* (2006)
Absolute Fit	Chisq	P > 0.05	Wheaton *et al* (1977)
	RMSEA	RMSEA < 0.08	Steiger & Lind (1980), Steiger (1990) Browne & Crudeck (1993)
	GFI	GFI > 0.9	Jöreskog & Sorbom (1984)
Incremental Fit	AGFI	> 0.9	Tanaka & Huba (1985)
	CFI	> 0.9	Bentler (1990), Hu & Beltler (1999)
	TLI	> 0.9	Bentler & Bonner (1980)
	NFI	> 0.9	Bentler (1989)
Parsimonious fit	Chisq/df	Chisq/df< 5.0	Marsh & Hocevar (1985)

The root mean square error of approximation (RMSEA) is said to be bounded below by zero. Steiger (1990) and Browne & Cudeck (1993) have defined "close fit" of a model, as a model with a$RMSEA \leq 0.05$. $RMSEA\ values \leq 0.05$ can be considered as a *good* fit, values between $0.05 \leq RMSEA \leq 0.08$ as an *adequate* fit, and values between $0.08 \leq RMSEA\ 0.10$ as a *mediocre* fit, whereas RMSEA values > 0.10 are *not acceptable*. Although there is general consensus that $RMSEA < 0.05$ for a good model, Hu & Bentler (1999) suggested an $RMSEA < 0.06$ as a cut-off criterion. As a rule of thumb, and $SRMR < 0.05$ suggests a good fit (Hu & Bentler, 1995), whereas $values < 0.10$ may be interpreted as an *acceptable* model fit.

Table 3.4: Different conditions for goodness-of-fit

	N < 250			***N > 250***		
Index	***m ≤ 12***	***12 ≤ m ≤ 30***	***m ≥ 30***	***m < 12***	***12 < m < 30***	***m ≥ 30***
χ^2	Insignificant p-values expected	Significant p-values even with good fit	Significant p-values expected	Insignificant p-values even with good fit	Significant p-values expected	Significant p-values
CFI or TLI	0.97 or better	0.95 or better	Above 0.92	0.95 or better	Above 0.92	Above 0.90
RNI	May not diagnose misspecification well	0.95 or better	Above 0.92	0.95 or better, not used with N > 1000	Above 0.92, not used with N > 1000	Above 0.90, not used with N > 1000
SRMR	Biased upward, use other indices	0.08 or less (with CFI of 0.95 or higher)	Less than 0.09 (with CFI above 0.92)	Biased upward; use other indices	0.08 or less (with CFI above 0.92)	0.08 or less (with CFI above 0.92)
RMSEA	Values < 0.08 with CFI = 0.97 or higher	Values < 0.08 with CFI of 0.95 or higher	Values < 0.08 with CFI above 0.92	Values < 0.07 with CFI of 0.97 or higher	Values < 0.07 with CFI of 0.92 or higher	Values < 0.07 with CFI of 0.90 or higher

m = number of observed variables; N = number of observations per group when applying CFA to multiple groups at the same time.

3.6 Partial Least Squares

This methodology as mentioned is variance-based, as opposed to the covariance-based SEM. It is separated into main branches, namely, partial least squares regression (PLS-R) and partial least squares correlation (PLS-C). The following sections discuss the steps followed in executing the algorithm.

3.6.1 Model specification

The vector of indicators $\boldsymbol{y}$ is composed of at least two subvectors, each measuring a unique latent variable, and each subvector contains at least two components. For the i*th* sub-vector $\mathbf{y_i}$ we have where the loading vector $\boldsymbol{\lambda_i}$ and the vector of errors ϵ_i have the same dimensions asyi, and the unobservable latent variable η_i is real-valued. This variable is represented as in equation (3.14). For convenience, the sufficient but by no means necessary assumption is made that all components of all error vectors are mutually independent, and independent of all latent variables. Latent variables have zero mean and unit variance. The correlations between η_i and η_j are denoted by ρ_{ij}. They are collected in a matrix $\boldsymbol{\Phi}, \boldsymbol{\Phi} := (\rho ij)$. At this stage, the nature of the relationships between the latent variables–whether linear or nonlinear–is not relevant. A particular set of easy implications is that the covariance matrix Σ_{ii} of y_i can be written as:

$$\sum_{ii} := Ey_i y_i^T = \lambda_i \lambda_i^T + \Theta_i, \tag{3.26}$$

where Θ_i, the covariance matrix of the measurement errors of the i*th* latent variable, is diagonal with non-negative diagonal elements, and we have for the covariance between y_i and $y_j$leads to the following equation:

$$\sum_{ij} := Ey_i y_j^T = \rho_{ij} \lambda_i \lambda_j^T . \tag{3.27}$$

The sample counterparts of Σ_{ii} and Σ_{ij} are denoted by S_{ii} and S_{ij}, respectively. The sample data are assumed to be standardized before being analysed. Therefore, the observed data has zero mean and unit (sample) variance. Note that the assumptions made so far entail that the sample counterparts are consistent and asymptotically normal estimators of the theoretical variance and covariance matrices. PLS features a number of iterative *fixed-point* algorithms, of which the mode $\boldsymbol{A}$ algorithm is selected. In general, the mode $\boldsymbol{A}$ (Figure 3.6) algorithm is numerically the most stable algorithm. For further discussions on the other PLS mode (Mode B) (Lohmoller, 1989; Henseler & Sarstedt, 2012).

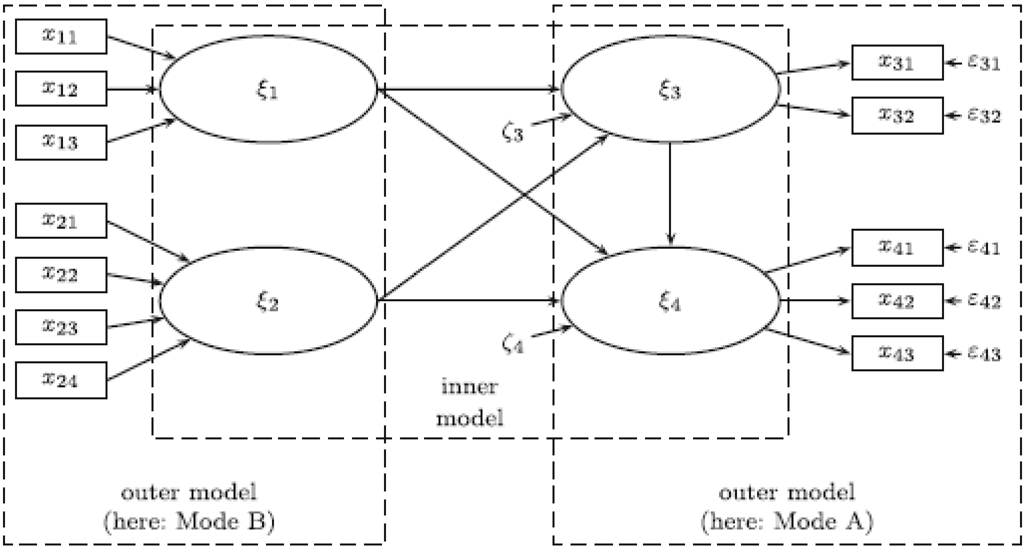

Figure 3.6: A simple partial least squares path model

3.6.2 PLS assumptions

All indicators have zero mean and unit variance only when data have been standardised or transformed. This method can be used when sample data are non-normal and sample size is small. That means it is a distribution-free technique. These are more relaxed restrictions than in SEM. See Gaskin (2012); Gaskin and Lowry (2014); Asyraf and Afthanorhan (2013), Ghulami, Ab Hamid & Zakaria (2014) and Hair *et al*., 2014) for sample size requirements. Multicollinearity barometer is the same as in SEM. The study will take these assumptions into account when applying the PLS algorithm to the sample data.

3.6.3 Model identification

No initiation values are especially necessary with PLS, as misidentification can be dealt with using the embedded partial least squares' confirmatory tetrad analyses (PLS-CTA) as cited in Roos (2014) and HTMT criterion (Henseler, 2015) and setting the centroid scheme for algorithms in smartPLS 3.0. This feature makes PLS a useful tool in developing or testing new theory. However, when using weighting scheme (Henseler *et al.,* 2009; Henser, 2010) the initiation value of 1 is set for initial values for each of the outer weights. Confirmatory tetrad analysis (CTA) (Bollen & Ting, 1993) may be useful to researchers who are facing identification problems. A structural equation model that is not identified in terms of its parameters may still be identified in terms of vanishing tetrads. So a researcher may be able to derive fit information for the model based on tetrad analysis.

Confirmatory tetrad analysis evaluates a proposed structural equation model by determining whether the vanishing tetrads implied by the model are really present, within sampling error. Spirtes, Glymour & Scheines' (1993) TETRAD II package explores a covariance matrix, looking for models that are consistent with it. Thus, their work presents an exception to the generally confirmatory character of SEM. Ting (1995) describes a SAS macro, called CTA-SAS, which performs this analysis. The exploratory tools developed by Spirtes *et al.* may be useful to modellers facing a covariance matrix with little prior information. However, these tools may also be useful in a confirmatory context. Researchers may wish to evaluate fit information for one model in light of fit information for other models. If many models fit a data set well, then the good fit of one model would seem to offer less compelling evidence in favour of the theory that inspired the model.

While structural equation modeling works generally at the level of variances and covariances, tetrad analysis works with relations between sets of four covariances at once. This procedure might also be sued to find equivalent models empirically (Bollen& Ting 1993, Ting 1995, and Spirtes, Glymour & Scheines, 1993). The use of confirmatory tetrad analysis in PLS (CTA-PLS; Gudergan *et al.*, 2008) allows distinguishing between formative and reflective measurement models. In principle, the analysis follows Bollen and Ting's (2000) confirmatory approach of testing model-implied vanishing tetrads in the PLS-SEM context with the difference that a bootstrapping procedure is applied to test the significance of the model-implied tetrads. Gudergan *et al.* (*ibid.*) describe the CTA-PLS procedure in detail. The implemented procedure needs at least 4 manifest variables per construct and can handle a maximum of 25 manifest variables per construct because of the exponentially increasing number of tests if a tetrad is redundant or not.

3.6.4 Parameter estimation

PLS modeling maximizes the correlation-based (Mode B) criterion as cited in (Hanafi, 2007) or maximize a covariance-based (Mode A) criterion (Tenenhaus & Tenenhaus, 2011). The following steps are to be followed for the partial least squares path model (PLS-PM) algorithm (Wold, 1982 & Lohmoller, 1989). The factor scores are estimated by an iterative procedure. This technique maximises the covariances between a series of latent variables and manifest variables, and as such, latent variables should not be correlated with each other. It follows a two-step approach which includes; in step one, the five-step iterative algorithm estimating inner weights and the final step involves estimation of path coefficients and outer loadings (Henseler & Ringle, 2012).

The steps involve: (a) outer approximation of the latent variable scores, (b) estimation of inner the weights, (c), inner approximation of the latent variables scores, using either the centroid, the path weighting or factorial scheme (d) estimation of the outer weights, and (e) model modification. Reinartz *et al*. (2009), Ringle *et al*. (2009) and Hair *et al*. (2011.a) all suggest PLS-PM when theory tested is weak or solely for prediction. Consistent PLS can estimate parameters of non-recursive model, of which SEM cannot (Dijkstra & Henseler, 2014). PLS uses path coefficients' effect sizes f^2 (Cohen, 1988), which are: 0.02, 0.15, and 0.35, for weak, moderate, and strong effects, respectively. The stop criterion of $< 10^{-5}$ (Wold, 1982) and maximum number of iterations (Ringle *et al*., 2005) until the criterion converges are also set.

To test the significance of the estimated parameter, bootstrapping (Efron, 1981) is performed. In bootstrapping, sub-samples are created with randomly drawn observations from the original set of data (with replacement). The subsample is then used to estimate the PLS path model. This process is repeated until a large number of random sub-samples have been created, typically ≥ 5,000 (Hair *et al.*, 2011). The parameter estimates, for example, outer weights, outer loadings and path coefficients; estimated from the subsamples are used to derive standard errors for the estimates. With this information, t-values are calculated to assess each estimate's significance. This algorithm is used also for construct validity. Hair *et al*. (2014) explain bootstrapping in more detail.

3.6.5 Measurement and Structural Model Validity

Validation is done simultaneously in smartPLS 3.0. The *convergence, discriminant and construct and nomological validity* of a PLS model fit assessment fit indices are summarised in Table 3.5 In addition, the consistent PLS in (smartPLS 3.0) statistical package setting or estimation is set (Dijkstra, 2015) for construct validation in the measurement model. The consistent PLS (PLSc) algorithm corrects reflective constructs' correlations to make them consistent with a factor-model (Dijkstra, 2010; Dijkstra, 2014; Dijkstra & Henseler, 2015) and when path estimates inconsistencies due to PLS in case of reflective constructs, which can adversely affect hypotheses testing results. The composite reliability measure of ≥ 0.70 is used instead of the Cronbach's alpha (Bagozzi & Yi, 1988). Indicator reliability is deemed acceptable with loadings of ≥0.70 (Hulland, 1999).

Table 3.5: Partial Least Squares Model Fit Indices

Category	Index name	Level of acceptance
Convergent Validity	AVE	> 0.5
Construct Validity	GFI	≥ 0.90
	CFI	≥ 0.90
	RMSEA	< 0.08
	Chisq/df	< 5.0
Discriminant Validity	$\sqrt{AVE}$	Correlation between constructs below 0.85

Henseler, Ringle and Sarstedt (2015) show by means of a simulation study that the Fornell-Larcker criterion and the examination of cross-loadings do not reliably detect the lack of discriminant validity in common research situations. These authors therefore propose an alternative approach, based on the multitrait-multimethod matrix, to assess discriminant validity: the heterotrait-monotrait ratio of correlations (HTMT) represented by Figure 3.7. Henseler, Ringle and Sarstedt (2015) demonstrate this approach's superior performance by means of a Monte Carlo simulation study, in which they compare the new approach to the Fornell-Larcker criterion and the assessment of (partial) cross-loadings. Finally, they provide guidelines on how to handle discriminant validity issues in variance-based structural equation modeling. See Henseler *et al.* (2015) for detailed explanations of the HTMT criterion for discriminant validity assessment in variance-based structural equations modeling.

3.6.6 Model Fit Assessment

Generally, all the model fit assessment indices in Table 3 are used in PLS as well, and these include using the Cronbach's alpha for indicator and construct reliability. The critical ratio criterion, as well as the composite reliability, is also used (Gaskin, 2012; Gaskin & Lowry, 2014; Ashram & Afthanorhan, 2013, Ghulami, Ab Hamid & Zakaria, 2014). However, Tenenhaus *et al.* (2004) proposed an index (goodness-of fit index (GoF)), which takes both measurement and structural model's fit into account. For more on the index, the reader may look into the following studies (Tenenhaus, 2005; Chin 2010).

3.6.7 Model modification

When the structural model somehow exhibits parsimony or has a lack-of-good fit with the hypothesised one, then re-specifying the model might be necessary. This can be done, according to Suhr (2006), by freeing fixed parameters (deleting insignificant paths) or fixing freed parameters (drawing paths that were absent from the hypothesized model). Remediation can be due to re-specification or truncating the model on more relevant theory and excluding redundant measured variables. PLS methodology will be used primarily as a tool to remedy SEM constraints and prediction after the structural model are attained after SEM application to the sample data, and apply PLSc, PLS-CTA and HTMT criterion to ensure best fit of the measurement and structural model.

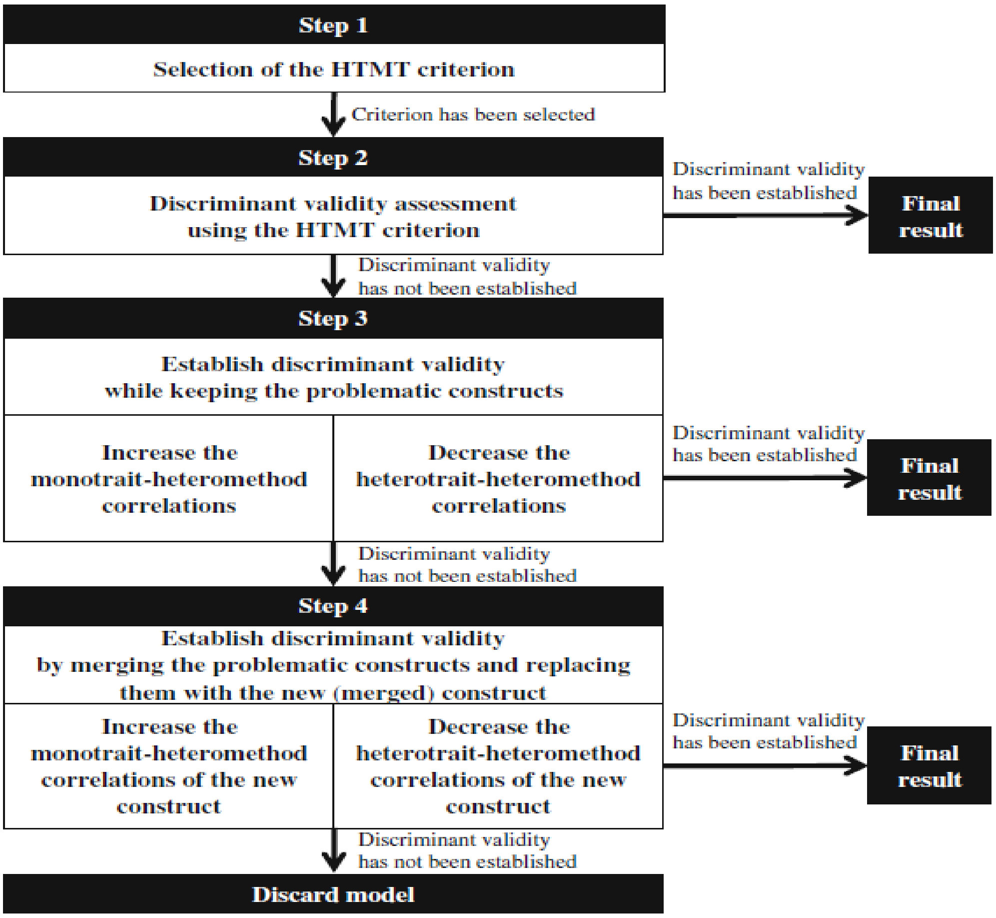

Figure 3.7: The HTMT Discriminant Validity steps in SEM. Adapted from Henseler*et al*., (2015:130).

3.7 Chapter summary

The aim of this chapter was to outline and discuss important methodological capabilities for SEM and PLS in analysing multivariate data by discussing test statistics and fit indices to be utilised in the next chapter. As well, the chapter explained the variables or instrument items to be used in the study. Furthermore, the chapter highlighted research design issues for SEM and PLS. The text also cited recent advancements in dealing with some of the shortcomings of SEM, in case remaining constructs cannot be used to estimate parameters, by using PLS method. The most frequent are model identification, discriminant and construct validity. It notes the similarities in the type of model assessment fit indices used for both SEM and PLS, with the addition of a few more for PLS in PLSc, PLS-CTA and HTMT criteria. If no identification problems are encountered, the SEM will be estimated using the PLS method and comparing the parameter estimates as well as construct similarities or differences.

Since the study does not anticipate any identification issues, the PLSc and PLS-CTA algorithms and the HTMT criterion was applied as remediation when the model did not confirm theory as tested by SEM. Yet it should be noted that this algorithm is used even when improving or developing new theories. Any contracting information in results, especially the final model, is reported accordingly as a gap that needs further exploration by keen researchers. The result is reported in *Chapter 4* of this study, bearing in mind the set hypotheses, research questions and objectives set in Chapter 1 and hopefully make a meaningful contribution to literature and theory as discussed in Chapter 2, by attending to the gaps of one methodology (SEM) by the other (PLS).

Chapter 4

Data Analysis

4.1 Introduction

This chapter gives the results of the data in relation to the hypothesised model, Figure 1 in Chapter 1. As discussed in earlier chapters, this study applied a two-step approach in running the structural equation model. The first step involves measurement model evaluation achieved using CFA (or EFA in case of model re-specification (Suhr & Shay, 2009)). The structural model is tested in the second stage to examine the hypotheses proposed in Chapter 1 of this study, and to attempt to respond to research questions and address objectives as outlined in that chapter as well. The interpretation is based on the underlying theoretical framework which is represented by Figure 1.1 in Chapter 1. The study adopted the SEM (for primary analysis) and PLS (for possible remedial properties) methodologies. Thus, this chapter is divided into two main sections; that of CFA-SEM results and another for PLS results. The last section provides concluding remarks about the results. It sometimes happens that the model fit assessment fails or does not meet the model fit indices criteria cut-off values. Due to the magnitude of some of the tables, for an example, the correlation and covariance matrix, some tables could not be included.

4.2 Preliminary Data Analysis

The univariate analysis of data was run using the SAS 9.3 PROC UNIVARIATE statement and SPSS was also used to generate some of these results. If skewness is between $-\frac{1}{2}$ and $+\frac{1}{2}$, the distribution is approximately symmetric and kurtosis <3 is called platykurtic, that is, the responses are highly dispersed or most responses share about the same amount of frequency. This kind of distribution is less peaked than the mesokurtic (normal) distribution. Table 4.1 shows the simple statistics of the data, with the univariate skewness and kurtosis measures showing a somewhat symmetrical and platykurtic distribution this implies that the data distribution is somewhat normal. Table 4.2 shows that the mean scaled univariate kurtosis is smaller than lower bound -0.039215686, this is mainly due to leptokurtic cases where the respondent selected 4 for "Neither agree nor disagree". Multivariate kurtosis results also reveal that the data were multivariate kurtose as this value is expected to be as close to zero as possible. The distribution of responses to the scale items is sparsely distributed.

Table 4.1: Simple Statistics

Variable	Mean	Std Dev	Skewness	Kurtosis
A1	4.33448	2.03482	-0.32187	-1.05403
A2	3.61235	1.92398	0.24339	-1.00905
A3	3.61578	1.99481	0.16172	-1.15193
A4	4.06346	2.06037	-0.07127	-1.27371
A5	3.44940	2.16512	0.32087	-1.25438
A6	3.50772	2.03057	0.30571	-1.09083
A7	4.08233	2.15070	-0.08930	-1.33235
A8	4.65352	1.86485	-0.46574	-0.70227
A9	3.31218	2.13029	0.40782	-1.21931
A10	3.21955	2.01792	0.44585	-0.99640
A11	3.65180	2.17069	0.19996	-1.34802
A12	3.50257	2.04828	0.31049	-1.11473
A13	4.25043	1.97207	-0.18965	-1.03638
A14	3.60720	2.13587	0.21252	-1.30879
A15	3.98456	2.10173	-0.09321	-1.26528
A16	3.97256	1.80661	0.03228	-0.80254
A17	3.59177	1.94284	0.22197	-0.98429
A18	4.30703	2.10548	-0.21951	-1.23446
A19	3.71355	1.99534	0.15669	-1.08543
A20	4.00515	1.96664	-0.01536	-1.12758
A21	3.57976	2.17058	0.26658	-1.29250
A22	3.99314	1.81913	-0.00698	-0.88798
A23	4.45455	1.98125	-0.34740	-1.05677
A24	4.24357	1.87927	-0.21674	-0.92476
A25	3.64494	2.02115	0.18158	-1.12859
A26	3.99485	1.75030	-0.01334	-0.67270
A27	3.71527	1.96566	0.16716	-1.09578
A28	4.18525	1.92112	-0.09713	-1.00375
A29	3.64322	2.34476	0.19785	-1.50460
A30	5.50772	1.66308	-1.11779	0.55642
A31	5.48542	1.61161	-1.03263	0.34828
A32	5.71184	1.54963	-1.27129	1.00019
A33	5.86964	1.64144	-1.47186	1.24056
A34	5.16123	1.86432	-0.80114	-0.38514
A35	4.85420	1.97084	-0.61226	-0.74376
A36	5.26244	1.78426	-0.94223	0.05379
A37	4.99485	1.99698	-0.71382	-0.67509
A38	3.61750	2.18307	0.21750	-1.33372
A39	4.07719	2.04399	-0.12766	-1.13822
A40	4.01029	2.08823	-0.02392	-1.24210
A41	3.91424	2.00502	0.02318	-1.13122
P2	4.33791	1.81083	-0.22535	-0.81379
P3	4.30875	1.84000	-0.14288	-0.96071
P4	4.09262	1.82244	-0.11724	-0.95344
P12	4.42710	1.64695	-0.26212	-0.45730
P13	4.89880	1.72561	-0.54567	-0.44949
P14	4.56775	1.73159	-0.37060	-0.62890
P15	4.16981	1.81356	-0.16043	-0.86885
P16	4.75815	1.83929	-0.48552	-0.72216

A correlation matrix is not invertible if its determinant is equal to 0, that is, it is not factorable as cited in (Field, 2012: p771). Also shown in Table 4.2 is that the determinant of the correlation matrix is not 0, but very close to zero. This could be due to the nature of the statements being related in one way or the other, giving rise to a hint of multicollinearity amongst variables. This is expected in psychometric testing questionnaires

Table 4.2: Factorability and Multivariate Normality

Mardia's Multivariate Kurtosis	371.7651
Relative Multivariate Kurtosis	1.1488
Normalized Multivariate Kurtosis	63.4855
Mardia Based Kappa (Browne, 1982)	0.1488
Mean Scaled Univariate Kurtosis	-0.2807
Adjusted Mean Scaled Univariate Kurtosis	-0.0135
Multivariate Mean Kappa (Bentler, 1985)	-2.3770
Multivariate LS Kappa (Bentler, 1983)	-0.0661
Determinant	3.704E-9

Table 4.3: Sphericity and Adequacy

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.884
Bartlett's Test of Sphericity	Approx. Chi-Square	10965.571
	df	1176
	Sig.	.000

According to Table 4.3, KMO = 0.884 suggests that the sample is adequate for confirmatory factor analysis, and the Bartlett's test of sphericity has a statistically significant $\chi^2 = 10965.571$, implying also that the sample size drawn is adequate for factor analysis.

4.3 Structural Equation Modeling results

Confirmatory factor analysis was run on the proposed statistics attitudes-outcomes model (SA-OM) and SATS-36 structure. The results are presented in Tables 4.4 to 4.7. The cut-off criterion is set at absolute 0.3 for factor loadings as discussed in Chapter 3. SAS 9.3 PROC FACTOR with PROMAX rotation resulted in PCF < 0.001 implying that the null hypothesis that the hypothesised model fits the sample data is rejected in favour of the alternative hypothesis. The null hypothesis asserts acceptable to good fit if the PCF > 0.80 to 1.00, respectively, but bad to unacceptable fit if PCF < 0.80.

Hypothesized model

All models in Table 4.4 were obtained using ML estimation. Table 4.4 presents model assessment indices as obtained from the SAS output. According to the output, the hypothesized model indices fall way below the acceptable levels. A χ^2 value < 0.0001 **(**significant) is recorded, implying bad model fit. The model has an SRMR that is> 0.08, RMSEA is > 0.05 but less than 0.08 suggesting adequate fit, the probability of close fit (PCF) is < 0.0001 which is a sign of no fit at all. The other fit indices such as the GFI = 0.7040, AGFI = 0.6701, CFI = 0.6783 and BBNFI = 0.6145 are below the suggested acceptance value of 0.90. Owing to the discrepancies, that is, with only one of the indices (RMSEA) suggesting good fit whilst the rest suggest otherwise, it is concluded that the hypothesised model does not fit the sample data well. The next step would be to run EFA to determine the factor structure of the sample data.

Modified models

This step is a result of under-fitting or over fitting the hypothesised structural model. The step involves either of the following: (a) truncating or re-specifying the model, (b) deleting cases, (c) or deleting variables that were marked during the preliminary data analysis process. Improvements were made to hypothesised model as stated in Table 4.6. All modified models have a significant chi-square value at < 0.0001, for bad fit. The SRMR < 0.08 for acceptable to good fit, whilst the RMSEA ranges between 0.05 and 0.08 for good fit. The 0.60 ≤ PCF < 0.0001 with a small probability implying bad to no fit, whereas a PCF = 0.6684 or 66.84% suggest a better fit than the rest of the models. The fit indices range from 0.8400 to 0.8806, obtained from deletion of observations that contributed immensely to the overall negative impact of the kurtosis on data. Model ML6 from Table 4.4 has a CFI = 0.8792 and BBNI rho-1 = 0.8806, closer to the 0.90 cut-off criterion which implies acceptable fit of the model.

Due to the unacceptable or no fit of the hypothesized model, EFA was done to determine the factor structure of the sample data. Using the SAS 9.3 PROC FACTOR, ML estimation was applied to the data to obtain Table 4.5. The table gives summary about the factors, variables that load into them, and their Cronbach’s alpha values. Factor 1 had a very good alpha equal to 0.8271, factor 2 has an alpha = 0.8647 suggesting that variables loading into it measure the same attribute. Factor 3 with a very good $\alpha = 0.8709$, Factor 4 has an acceptable α = 0.7975, and Factor 5 a questionable α = 0.6113. Cronbach's α = 0.7614 suggests that Factor 6 is acceptable, Factor 7 has a very good α = 0.8137, Factor 8 with an acceptable α = 0.7971, and finally Factor 9 with a questionable α = 0.6370.

The CFA results due to the hypothesised model and the EFA results are compared in Table 4.6 with their old and new names as suggested by variables loading into them. EFA results suggest that seven of the nine factors are valid, as opposed to the *a priori* model which suggests that only two of the nine factors are valid. The number of factors retained is based on the Kaiser criterion of factor retention, suggests that only factors with eigenvalues greater than 1 are retained. This is represented in Table 4.7. It should be noted that some of the factors are under-identified, that is, have less than three variables loading into them. The initial (hypothesized) and modified (ML6) model estimates are given in appendix B, Table A and B. The results in Table A have only one insignificant covariance between interest and self-efficacy. On the other hand, the modified model has two insignificant covariances between cognitive competence and difficulty, also, between anxiety and effort.

Table 4.4: Model Fit Assessment under SEM

Index	Hypothesised model	ML1	ML2	ML3	ML4	ML5	ML6	ML7
Number of Variables	49	41	41	41	35	37	41	35
Number of Cases	583	583	583	583	583	583	448	547
Exclusions	None	8 variables	8 variables	8 variables	14 variables (including previous 8) and 1 latent variable	12 variables (including previous 8)	8 variables and 135 cases	14 variables (including previous 8) and 35 cases
Absolute Fit Indices								
χ^2	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
SRMR	0.11327	0.0569	0.0587	0.0673	0.0611	0.0708	0.0585	0.0569
GFI	0.7040	0.8574	0.8547	0.8400	0.8622	0.8475	0.8534	0.8589
Parsimony Fit Indices								
AGFI	0.6701	0.8303	0.8316	0.8171	0.8358	0.8207	0.8301	0.8250
PGFI	0.6579	0.7548	0.7744	0.7689	0.7650	0.7595	0.7733	0.7269
RMSEA	0.0714	0.0502	0.0518	0.0528	0.0553	0.0571	0.0491	0.0528
PCF	< 0.0001	0.4391	0.1438	0.0383	0.0040	< 0.0001	0.6684	0.0669
Incremental Fit Indices								
CFI	0.6783	0.8741	0.8710	0.8528	0.8728	0.8539	0.8792	0.8751
BBNFI	0.6145	0.8071	0.8062	07837	0.8161	0.7946	0.7927	0.8114
BBNNI	0.6557	0.8570	0.8576	0.8392	0.8566	0.8370	0.8667	0.8525
BBNNI- rho 1	0.5875	0.8755	0.8721	0.8540	0.8739	0.8552	0.8806	0.8770

Table 4.5: Exploratory Factor Analysis

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9	Cronbach's alpha
CC_2	66									
CC_1	64									
A_3	60									
A_4	30									
A_2	56									
D_2	55									0.8271
V_5	50									
A_6	50									
V_1	46									
CC_6	40									
CC_3	32									
SE_4		86								
SE_5		80								
SE_2		77								0.8647
SE_3		75								
SE_6		67								
SE_1		43								
I_3			92							
I_2			81							0.8709
I_1			75							
I-4			71							
E_2				84						
E_3				80						0.7975
E_4				64						
E_1				48						
D_4					64					
D_6					56					0.6113
D_7					52					
D_5					40					
A_5						54				
CC_5						39				
A1						37				0.7614
CC_4						35				
V_6						34				
AN_1							86			0.8137
AN_2							78			
SO_3								75		0.7971
SO_2								58		
V_9									55	
A_7									39	0.6370
V_8									38	

****Note: The default factor loadings in SAS 9.3 are multiplied by 100 on**

Table 4.6: Reliability Results

Construct According to SATS-36/MPSP	Initial Reliability values after CFA	Comment	Construct after EFA	Reliability values after EFA	Comment
Affect	0.6181	Questionable	**Relevance & Motivation**	0.8271	Very good
Cognitive Competence	0.4252	Unacceptable	**Self-Efficacy**	0.8647	Very good
Difficulty	0.5511	Poor	**Interest**	0.8709	Very good
Effort	0.7975	Good	**Effort**	0.7975	Good
Interest	0.6918	Questionable	**Difficulty**	0.6113	Questionable
Self-Efficacy	0.8647	Very good	**Motivation**	0.7614	Good
Value	0.4670	Unacceptable	**Anxiety**	0.8137	Very Good
Statistics Outcome	0.5145	Poor	**Statistics Outcome**	0.7971	Good
Anxiety	0.4978	Unacceptable	**Value**	0.6370	Questionable

Table 4.7: Eigenvalue and Variance Proportion

Factor	Eigenvalue	Difference	Proportion	Cumulative
1	21.5606120	12.4390066	0.4030	0.4030
2	9.1216054	2.5219210	0.1705	0.5735
3	6.5996844	1.9919977	0.1234	0.6968
4	4.6076867	0.5069741	0.0861	0.7829
5	4.1007126	1.2371463	0.0766	0.8596
6	2.8635663	0.9382439	0.0535	0.9131
7	1.9253224	0.3084158	0.0360	0.9491
8	1.6169066	0.5097774	0.0302	0.9793
9	1.1071293	0.3020323	0.0207	1.0000

Table 4.8: Initial Model Fit Assessment

Construct	Cronbach's alpha	Comment	Composite reliability	Comment	AVE	Comment	Verdict
Affect	0.497	Unacceptable	0.392	Unacceptable	0.348	Unacceptable	Not Valid
Anxiety	0.814	Very good	0.915	Excellent	0.843	Acceptable	Valid
Cognitive Competence	0.425	Unacceptable	0.111	Unacceptable	0.311	Unacceptable	Not Valid
Difficulty	0.560	Poor	0.702	Acceptable	0.382	Unacceptable	Not Valid
Effort	0.798	Good	0.869	Very Good	0.626	Acceptable	Valid
Interest	0.692	Questionable	0.811	Very Good	0.587	Acceptable	Valid
Self-Efficacy	0.865	Very Good	0.898	Very Good	0.596	Acceptable	Valid
Statistics Outcome	0.515	Poor	0.743	Acceptable	0.558	Acceptable	Valid
Value	0.312	Unacceptable	0.107	Unacceptable	0.280	Unacceptable	Not Valid

4.4 Partial Least Squares results

SmartPLS 3.0 was used to obtain PLS results. Due to the model fit assessment indices under SEM being below the 0.90 cut-off criterion, PLS analysis was applied to the sample data to determine its modification capabilities. This technique, as discussed in earlier chapters can be used either as an exploratory, confirmatory, or model specification correction tool. Its analysis is grounded on construct, discriminant and convergent validity.

Table 4.8 gives the initial model assessment results as suggested by the hypothesised model. The Cronbach's alpha has a cut-off value ≥ 0.60 for the constructs. These range from 0.312 to 0.865, that is, unacceptable to very good reliability. PLS analysis looks at composite reliability for construct reliability with values ranging from 0.107 to 0.915, unacceptable to excellent reliability, respectively. Four of the nine constructs fall below the AVE ≥ 0.50 cut-off criterion, with the rest deemed acceptable, implying convergent validity. The overall construct validity suggests only five valid constructs have convergent validity.

According to Table 4.9 showing the discriminant validity results, there is no discrimination between affect and cognitive competence. This is shown by the values corresponding to the affect-column, where the first value (0.590) in the column is the less than the other value (0.676) in the same column. This implies that affect and cognitive competence may possibly measure the same thing. It is expected that the first number in a column be larger than the rest of the values in the same column to validate discrimination between any two construct. The path effects denoted by f^2 are an indication of how one construct impacts the other. Cohen's (1988) cut-off criteria are set at 0.02 for weak effect, 0.15 for moderate effect and 0.35 for stronger effect. Table 4.10 shows that difficulty has virtually no effect on anxiety, as with anxiety and cognitive competence on effort, difficulty on interest, and effort on self-efficacy. Also there is no effect of anxiety, cognitive competence and effort on statistics outcome, as well as effort on value. The blank spaces imply that these paths were not included in the hypothesized model.

These constructs show weak effects: anxiety on affect, affect on interest, cognitive competence on interest, difficulty and interest on self-efficacy, and self-efficacy on value. Likewise, the following paths exhibit moderate effects: anxiety on cognitive competence, interest on effort and value, and lastly self-efficacy has a strong effect on statistics outcome. A sample bootstrapping gave the results in Table 4.11, for the path coefficients. The default significance level is default at $\alpha = 0.05$ in smartPLS 3.0. The path coefficients with $\alpha > 0.05$ suggest that there is no effect of the construct on the left on the one on the right. There is no effect of anxiety on interest and statistics outcome, cognitive competence on effort and statistics outcome, difficulty on anxiety and interest, and effort on self-efficacy and value.

Table 4.9: Initial Discriminant Validity results

	Affect	Anxiety	Cognitive Competence	Difficulty	Effort	Interest	Self-Efficacy	Statistics Outcome	Value
Affect	**0.590**								
Anxiety	-0.393	**0.918**							
Cognitive Competence	**0.676**	-0.356	**0.558**						
Difficulty	0.344	0.045	0.387	**0.618**					
Effort	0.138	0.006	0.198	0.218	**0.791**				
Interest	0.468	-0.158	0.452	0.286	0.393	**0.766**			
Self-Efficacy	0.363	-0.186	0.422	0.364	0.200	0.383	**0.772**		
Statistics Outcome	0.321	-0.135	0.344	0.260	0.208	0.452	0.507	**0.747**	
Value	0.502	-0.095	0.466	0.424	0.183	0.515	0.411	0.513	**0.530**

Table 4.10: Initial f2 Effects

	Affect	Anxiety	Cognitive Competence	Difficulty	Effort	Interest	Self-Efficacy	Statistics Outcome	Value
Affect						0.059			
Anxiety	0.051		0.197		0.008	0.001		0.002	
Cognitive Competence	0.637				0.003	0.035		0.000	
Difficulty		0.002	0.229			0.010	0.087		
Effort							0.001	0.008	0.002
Interest					0.137		0.090		0.207
Self-Efficacy								0.135	0.079
Statistics Outcome									
Value								0.143	
Variable type	Endogenous	Endogenous	Endogenous	Exogenous	Endogenous	Endogenous	Endogenous	Endogenous	Endogenous

Table 4.11: Initial Bootstrapped Path coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Verdict
Affect -> Interest	0.306	0.309	0.059	5.214	0.000	supported
Anxiety -> Affect	0.170	0.167	0.036	4.756	0.000	supported
Anxiety -> Cognitive Competence	0.338	0.333	0.040	8.487	0.000	supported
Anxiety -> Effort	-0.086	-0.084	0.042	2.033	0.042	supported
Anxiety -> Interest	-0.051	-0.048	0.045	1.137	**0.256**	unsupported
Anxiety -> Statistics Outcome	0.038	0.038	0.038	0.998	**0.318**	unsupported
Cognitive Competence -> Affect	0.620	0.622	0.030	20.537	0.000	supported
Cognitive Competence -> Effort	0.052	0.053	0.045	1.168	**0.243**	unsupported
Cognitive Competence -> Interest	0.234	0.231	0.062	3.781	0.000	supported
Cognitive Competence -> Statistics Outcome	0.004	0.005	0.045	0.090	**0.928**	unsupported
Difficulty -> Anxiety	0.056	0.065	0.084	0.666	**0.506**	unsupported
Difficulty -> Cognitive Competence	0.459	0.462	0.035	13.288	0.000	supported
Difficulty -> Interest	0.038	0.040	0.057	0.672	**0.501**	unsupported
Difficulty -> Self Efficacy	0.301	0.303	0.043	7.022	0.000	supported
Effort -> Self Efficacy	0.040	0.044	0.045	0.903	**0.367**	unsupported
Effort -> Statistics Outcome	0.076	0.076	0.035	2.149	0.032	supported
Effort -> Value	-0.038	-0.039	0.040	0.939	**0.348**	unsupported
Interest -> Effort	0.383	0.384	0.045	8.570	0.000	supported
Interest -> Self Efficacy	0.280	0.278	0.047	5.974	0.000	supported
Interest -> Value	0.433	0.433	0.041	10.648	0.000	supported
Self-Efficacy -> Statistics Outcome	0.337	0.336	0.041	8.232	0.000	supported
Self-Efficacy -> Value	0.252	0.255	0.038	6.678	0.000	supported
Value -> Statistics Outcome	0.355	0.356	0.042	8.461	0.000	supported

Indirect path effects are as follows, as presented in Table 4.12: there is a weak indirect positive effect of interest on self-efficacy and value and of difficulty on self-efficacy, there is an indirect negative effect of difficulty on cognitive competence, anxiety on effort, self-efficacy, statistics outcome and value. Also, there is an indirect negative effect of effort on statistics outcome. Furthermore, there is a strong indirect positive effect of interest on statistics outcome. Total effects in Table 4.13 ranging from weak to strong effects are also computed, and are as follows: anxiety has a negative weak effect on effort, self-efficacy, statistics outcome and value. Effort has a positive weak effect on self-efficacy, statistics outcome and value. On the other hand, cognitive competence has a strong positive effect on affect and interest. Difficulty has a strong positive effect on cognitive competence and self-efficacy. Moreover, interest has a strong positive effect on effort, self-efficacy, statistics outcome and value. Furthermore, value has a positive but strong effect on statistics outcome. Lastly, anxiety has a strong positive effect on affect and cognitive competence.

Since most of the constructs are not valid and a number of path coefficients are found to be insignificant, the model was modified accordingly to produce Figure 4.1. Some variables were removed from the cognitive competence construct to form the new relevance and motivation construct. As well, affect has been changed to motivation after deletion of other variables that formed the affect construct. Table 4.14 shows that all but two Cronbach's alphas are ≥ 0.70. The two constructs with $\alpha < 0.70$ are effort and value. The composite reliability suggests that all the constructs show good to excellent composite reliability. The AVE values also show that all the construct convergence validity is established. The overall verdict implies that all nine constructs are valid. Discriminant validity is established as shown by the results in Table 4.15.

A mixture of weak to strong path coefficient effects are evident in Table 4.16 and are as follows: anxiety has a weak effect on effort, interest, motivation, relevance and motivation and statistics outcome. Difficulty has a weak effect on interest and self-efficacy, effort has a weak effect on self-efficacy, statistics outcome and value. On the other hand, difficulty has a strong effect on relevance and motivation, and motivation has a strong effect on interest. The results of bootstrapping shown in Table 4.17 show that almost half of the relationships or hypotheses are not accepted. The significance level is default in smartPLS 3.0 at $\alpha = 0.05$.

Likewise, in Table 4.18, thirteen of the twenty-three path coefficients are significant. Anxiety to effort path coefficient is insignificant. In contrast sixteen of the indirect path coefficients effects are significant. Difficulty to interest path coefficient is significant. Seventeen of the total path coefficients effects are significant. The total path coefficient effect of motivation to value is also significant.

Table 4.12: Initial Indirect Effects

Construct	Affect	Anxiety	Cognitive Competence	Difficulty	Effort	Interest	Self-Efficacy	Statistics Outcome	Value
Affect	1.000				0.112		0.090	0.090	0.146
Anxiety	-0.230	1.000			-0.086	-0.204	-0.050	-0.051	-0.086
Cognitive Competence			1.000		0.156	0.180	0.126	0.129	0.201
Difficulty	0.229		-0.017	1.000	0.122	0.157	0.078	0.197	0.193
Effort					1.000			-0.003	0.006
Interest						1.000	0.009	0.306	0.062
Self-Efficacy							1.000	0.089	
Statistics Outcome								1.000	
Value									1.000

Table 4.13: Initial Total Effects

Construct	Affect	Anxiety	Cognitive Competence	Difficulty	Effort	Interest	Self-Efficacy	Statistics Outcome	Value
Affect	1.000				0.112	0.294	0.090	0.090	0.146
Anxiety	-0.404	1.000	-0.374		0.001	-0.170	-0.050	-0.087	-0.086
Cognitive Competence	0.614		1.000		0.213	0.409	0.126	0.139	0.201
Difficulty	0.229	0.045	0.387	1.000	0.122	0.253	0.351	0.197	0.193
Effort					1.000		0.024	0.072	-0.032
Interest					0.380	1.000	0.305	0.306	0.496
Self-Efficacy							1.000	0.425	0.252
Statistics Outcome								1.000	
Value								0.353	1.000

Table 4.14: Final Model Fit Assessment

Construct	Cronbach's alpha	Comment	Composite reliability	Comment	AVE	Comment	Verdict
Anxiety	0.814	Very good	0.915	Excellent	0.843	Acceptable	Valid
Effort	0.548	Poor	0.768	Good	0.525	Acceptable	Valid
Interest	0.798	Good	0.869	Unacceptable	0.626	Acceptable	Valid
Motivation	0.871	Very good	0.912	Excellent	0.722	Acceptable	Valid
Relevance	0.713	Good	0.838	Very Good	0.633	Acceptable	Valid
& Motivation	0.763	Good	0.840	Very Good	0.513	Acceptable	Valid
Self-Efficacy	0.865	Very Good	0.898	Very Good	0.597	Acceptable	Valid
Statistics Outcome	0.797	Good	0.908	Excellent	0.831	Acceptable	Valid
Value	0.665	Questionable	0.817	Very Good	0.599	Acceptable	Valid

Table 4.15: Final Discriminant Validity

Construct	**Anxiety**	**Difficulty**	**Effort**	**Interest**	**Motivation**	**Relevance & Motivation**	**Self-Efficacy**	**Statistics Outcome**	**Value**
Anxiety	**0.918**								
Difficulty	-0.345	**0.725**							
Effort	-0.006	0.000	**0.791**						
Interest	0.136	-0.126	0.389	**0.850**					
Motivation	0.173	-0.122	0.273	0.560	**0.796**				
Relevance & Motivation	-0.378	0.620	-0.070	-0.212	-0.233	**0.716**			
Self-Efficacy	0.186	-0.094	0.201	0.383	0.555	-0.167	**0.773**		
Statistics Outcome	-0.143	0.100	-0.205	-0.461	-0.477	0.132	-0.506	**0.912**	
Value	0.079	-0.096	0.164	0.475	0.584	-0.185	0.459	-0.480	**0.774**

Table 4.16: Final f2 Effects

Construct	Anxiety	Difficulty	Effort	Interest	Motivation	Relevance & Motivation	Self-Efficacy	Statistics Outcome	Value
Anxiety			0.004	0.000	0.009	0.052		0.005	
Difficulty	0.136			0.000		0.465	0.003		
Effort							0.004	0.011	0.002
Interest			0.176				0.122		0.149
Motivation				0.401					
Relevance & Motivation			0.000	0.005	0.035			0.000	
Self-Efficacy								0.131	0.133
Statistics Outcome									
Value								0.111	

Table 4.17: Final Bootstrapped Path coefficients

Relationship	**Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**	**Verdict**
Anxiety -> Effort	-0.064	-0.063	0.042	1.535	0.125	unsupported
Anxiety -> Interest	0.010	0.009	0.043	0.235	0.814	unsupported
Anxiety -> Motivation	0.099	0.099	0.050	1.993	0.046	supported
Anxiety -> Relevance & Motivation	-0.186	-0.185	0.039	4.789	0.000	supported
Anxiety -> Statistics Outcome	-0.061	-0.061	0.040	1.513	0.130	unsupported
Difficulty -> Anxiety	-0.345	-0.347	0.041	8.337	0.000	supported
Difficulty -> Interest	-0.010	-0.010	0.047	0.211	0.833	unsupported
Difficulty -> Relevance & Motivation	0.556	0.558	0.035	15.923	0.000	supported
Difficulty -> Self Efficacy	-0.049	-0.050	0.041	1.201	0.230	unsupported
Effort -> Self Efficacy	0.064	0.063	0.049	1.311	0.190	unsupported
Effort -> Statistics Outcome	-0.088	-0.088	0.036	2.435	0.015	supported
Effort -> Value	-0.044	-0.043	0.040	1.100	0.272	unsupported
Interest -> Effort	0.395	0.398	0.041	9.634	0.000	supported
Interest -> Self Efficacy	0.352	0.354	0.046	7.615	0.000	supported
Interest -> Value	0.367	0.365	0.040	9.232	0.000	supported
Motivation -> Interest	0.540	0.540	0.033	16.287	0.000	supported
Relevance & Motivation -> Effort	-0.011	-0.010	0.041	0.259	0.796	unsupported
Relevance & Motivation -> Interest	-0.076	-0.077	0.045	1.698	0.090	supported
Relevance & Motivation -> Motivation	-0.196	-0.197	0.048	4.048	0.000	supported
Relevance & Motivation -> Statistics Outcome	-0.010	-0.012	0.037	0.281	0.779	unsupported
Self-Efficacy -> Statistics Outcome	-0.338	-0.338	0.042	7.980	0.000	supported
Self-Efficacy -> Value	0.327	0.330	0.037	8.720	0.000	supported
Value -> Statistics Outcome	-0.307	-0.308	0.041	7.553	0.000	supported

Path coefficients effects are deemed significant at the default 5% level of significance. Of the seventeen hypothesized paths, fourteen were significant and these are presented in Table 4.17. The paths from anxiety to motivation, relevance and motivation, difficulty to anxiety and relevance and motivation, effort to statistics outcome, interest to effort, self-efficacy and value were found to be significant. Moreover, significant path from motivation to interest, relevance and motivation to interest and motivation, self-efficacy to statistics outcome and value, and finally, value to statistics outcome were observed.

Table 4.18: Final Indirect Effects

Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Verdict
Anxiety -> Effort	0.040	0.028	0.037	1.096	0.273	unsupported
Anxiety -> Interest	0.087	0.059	0.071	1.232	0.218	unsupported
Anxiety -> Motivation	0.036	0.024	0.030	1.214	0.225	unsupported
Anxiety -> Relevance & Motivation						unsupported
Anxiety -> Self Efficacy	0.033	0.022	0.032	1.032	0.302	unsupported
Anxiety -> Statistics Outcome	-0.022	-0.010	0.025	0.878	0.380	unsupported
Anxiety -> Value	0.047	0.031	0.042	1.122	0.262	unsupported
Difficulty -> Anxiety						unsupported
Difficulty -> Effort	-0.042	-0.042	0.029	1.464	0.143	unsupported
Difficulty -> Interest	-0.135	-0.135	0.034	3.928	0.000	supported
Difficulty -> Motivation	-0.156	-0.156	0.029	5.318	0.000	supported
Difficulty -> Relevance & Motivation	0.064	0.064	0.015	4.360	0.000	supported
Difficulty -> Self Efficacy	-0.054	-0.054	0.016	3.268	0.001	supported
Difficulty -> Statistics Outcome	0.079	0.053	0.067	1.175	0.240	unsupported
Difficulty -> Value	-0.085	-0.085	0.024	3.478	0.001	supported
Effort -> Self Efficacy						unsupported
Effort -> Statistics Outcome	-0.014	-0.009	0.028	0.525	0.600	unsupported
Effort -> Value	0.021	0.021	0.016	1.281	0.200	unsupported
Interest -> Effort						unsupported
Interest -> Self Efficacy	0.025	0.025	0.020	1.291	0.197	unsupported
Interest -> Statistics Outcome	-0.308	-0.216	0.224	1.375	0.169	unsupported
Interest -> Value	0.106	0.108	0.026	4.146	0.000	supported
Motivation -> Effort	0.213	0.215	0.026	8.094	0.000	supported
Motivation -> Interest						unsupported
Motivation -> Self Efficacy	0.204	0.205	0.029	7.006	0.000	supported
Motivation -> Statistics Outcome	-0.166	-0.117	0.122	1.361	0.174	unsupported
Motivation -> Value	0.255	0.256	0.028	9.036	0.000	supported
Relevance & Motivation -> Effort	-0.072	-0.073	0.022	3.342	0.001	supported
Relevance & Motivation -> Interest	-0.106	-0.106	0.027	3.966	0.000	supported
Relevance & Motivation -> Motivation						supported
Relevance & Motivation -> Self Efficacy	-0.069	-0.070	0.022	3.196	0.001	supported
Relevance & Motivation -> Statistics Outcome	0.057	0.040	0.045	1.263	0.207	unsupported
Relevance & Motivation -> Value	-0.086	-0.086	0.026	3.318	0.001	supported
Self-Efficacy -> Statistics Outcome	-0.100	-0.071	0.074	1.349	0.178	unsupported
Self-Efficacy -> Value						unsupported

Value -> Statistics Outcome						unsupported

Table 4.18 gives bootstrapping results of both significant and insignificant indirect path coefficients effects. These effects are as follows: difficulty to interest, motivation, relevance and motivation, self-efficacy and value. The path from interest to values is significant. Also, motivation to effort, self-efficacy and value, as well as relevance motivation to effort, interest, self-efficacy and value were significant. The significant total path coefficients effects are presented in Table 4.19, and are as follows: the path from difficulty to interest, motivation, relevance and motivation, self-efficacy and value. Interest to effort, self-efficacy and value are all significant. Motivation to effort, interest, self-efficacy and value are all significant, as well as relevance and motivation to effort, interest, motivation, self-efficacy and value. Lastly, self-efficacy to value path coefficient effect is significant.

Table 4.19: Final Total Effects

Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Verdict
Anxiety -> Effort	-0.024	-0.014	0.043	0.553	0.580	unsupported
Anxiety -> Interest	0.097	0.064	0.087	1.115	0.265	unsupported
Anxiety -> Motivation	0.135	0.092	0.110	1.224	0.221	unsupported
Anxiety -> Relevance & Motivation	-0.186	-0.124	0.143	1.301	0.193	unsupported
Anxiety -> Self Efficacy	0.033	0.022	0.032	1.032	0.302	unsupported
Anxiety -> Statistics Outcome	-0.082	-0.039	0.085	0.969	0.333	unsupported
Anxiety -> Value	0.047	0.031	0.042	1.122	0.262	unsupported
Difficulty -> Anxiety	-0.345	-0.232	0.261	1.326	0.185	unsupported
Difficulty -> Effort	-0.042	-0.042	0.029	1.464	0.143	unsupported
Difficulty -> Interest	-0.145	-0.145	0.040	3.659	0.000	supported
Difficulty -> Motivation	-0.156	-0.156	0.029	5.318	0.000	supported
Difficulty -> Relevance & Motivation	0.620	0.622	0.030	20.943	0.000	supported
Difficulty -> Self Efficacy	-0.103	-0.104	0.045	2.306	0.021	supported
Difficulty -> Statistics Outcome	0.079	0.053	0.067	1.175	0.240	unsupported
Difficulty -> Value	-0.085	-0.085	0.024	3.478	0.001	supported
Effort -> Self Efficacy	0.064	0.063	0.049	1.311	0.190	unsupported
Effort -> Statistics Outcome	-0.102	-0.072	0.084	1.225	0.221	unsupported
Effort -> Value	-0.023	-0.023	0.044	0.529	0.597	unsupported
Interest -> Effort	0.395	0.398	0.041	9.634	0.000	supported
Interest -> Self Efficacy	0.377	0.379	0.041	9.284	0.000	supported
Interest -> Statistics Outcome	-0.308	-0.216	0.224	1.375	0.169	unsupported
Interest -> Value	0.473	0.472	0.035	13.420	0.000	supported

Motivation -> Effort	0.213	0.215	0.026	8.094	0.000	supported
Relationship	**Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**	**Verdict**
Motivation -> Interest	0.540	0.540	0.033	16.287	0.000	supported
Motivation -> Self Efficacy	0.204	0.205	0.029	7.006	0.000	supported
Motivation -> Statistics Outcome	-0.166	-0.117	0.122	1.361	0.174	unsupported
Motivation -> Value	0.255	0.256	0.028	9.036	0.000	supported
Relevance & Motivation -> Effort	-0.083	-0.083	0.046	1.779	0.075	supported
Relevance & Motivation -> Interest	-0.182	-0.183	0.052	3.517	0.000	supported
Relevance & Motivation -> Motivation	-0.196	-0.197	0.048	4.048	0.000	supported
Relevance & Motivation -> Self Efficacy	-0.069	-0.070	0.022	3.196	0.001	supported
Relevance & Motivation -> Statistics Outcome	0.047	0.031	0.055	0.851	0.395	unsupported
Relevance & Motivation -> Value	-0.086	-0.086	0.026	3.318	0.001	supported
Self-Efficacy -> Statistics Outcome	-0.439	-0.303	0.321	1.368	0.171	unsupported
Self-Efficacy -> Value	0.327	0.330	0.037	8.720	0.000	supported
Value -> Statistics Outcome	-0.307	-0.216	0.223	1.376	0.169	unsupported

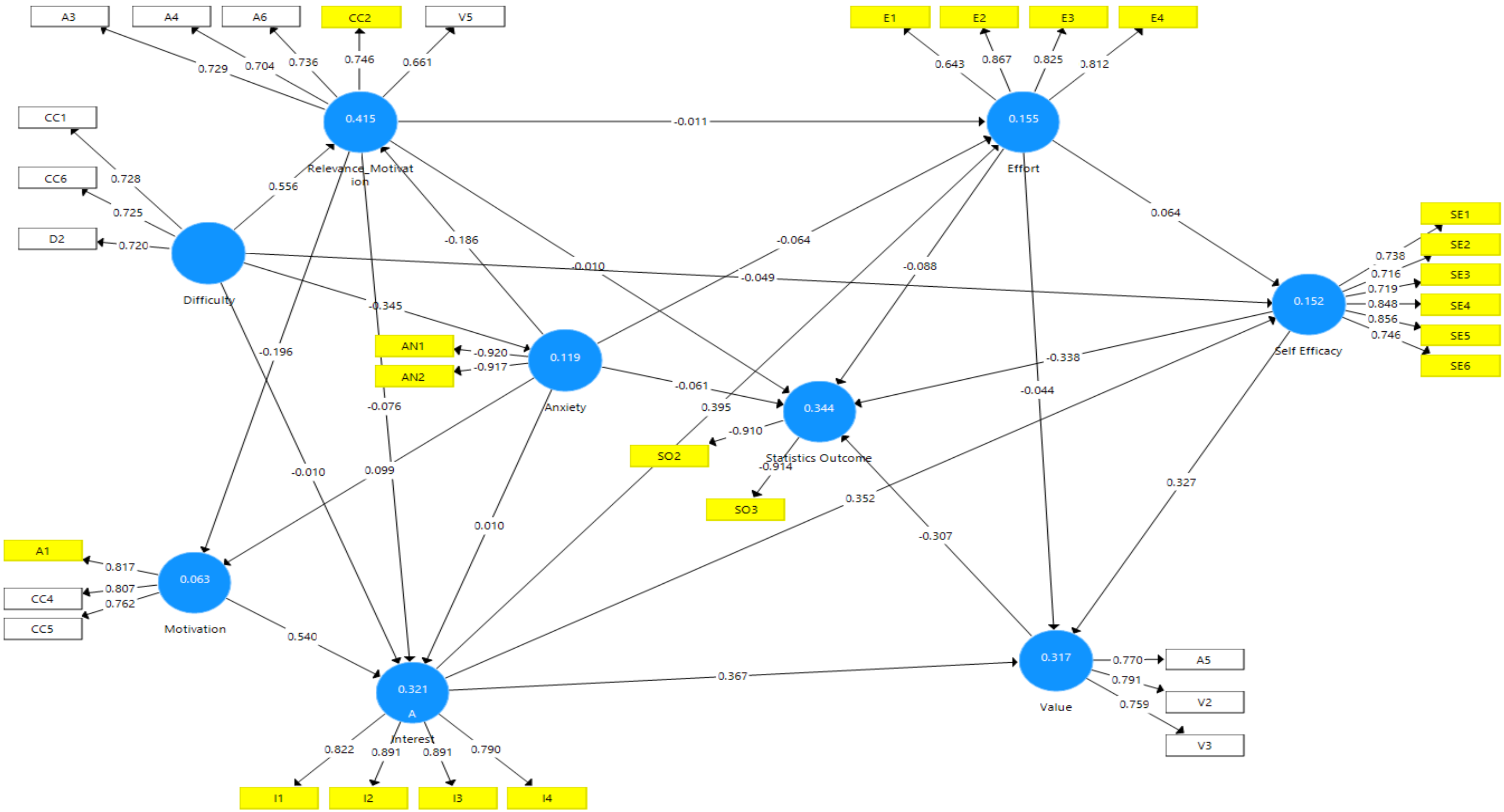

Figure 4.1: Final PLS analysis path model showing path coefficients

4.5 Summary

This chapter aimed to give an account of data output as produced from the sample data. The preliminary and primary data analyses results were presented. The SEM and PLS analysis steps of developing a model of better fit was followed by looking at the relevant model fit assessment indices. Only results deemed important in responding to the research questions and meeting study objectives were included. These results bear evidence of the sample data as obtained and may not be used to infer to the population. The general rules of thumb were taken into consideration when compiling the results.The construct validity results revealed the difference between the SAOM and SATS-36 factor structures. The results showed statistical significant relationship between two of the four self-efficacy constructs. The results also showed that there are relationships between current statistics self-efficacy and statistics outcome measures.

The results highlight the fact that students with high self-efficacy may see the relevance or value of the subject in the degree programme of their choice. All of the proposed hypotheses were found to be statistically significant although the validity results were all positive. It has been established according to the findings that there is virtually no effect of a student's anxiety on their statistics outcomes variable. It is also important to note that a decrease in the students' anxiety throughout their academic life has an impact in terms of the heightened perceived usefulness and their statistics achievement. The discussions, recommendations in the next chapter are based solely on the results reported in this chapter.

Chapter 5

Summary, Conclusions and Recommendations

5.1 Introduction

This chapter will look to give the summary of the objectives of the study, methodologies used herein, conclusions based on the findings in chapter four of the study and recommendations made to policy-makers and researchers. Primarily, this study applied SEM to investigate the effect of students' perceptions and attitudes on their self-efficacy and statistics outcome. Exploratory and confirmatory factor analyses were applied to the sample data collected during the second semester of the 2015 academic year. Respondents were students registered for statistics module at the NWU.

The findings of this study are intended to give guidance to instructors, policy makers and researchers in identifying variables (including somewhat redundant ones) that need to be developed further, monitored and require student-instructor attention. Moreover, the study has identified shortcomings of large data volumes with many observed variables. The study has established possible use of Partial Least Squares analysis as a remedial tool in curing SEM model identification deficiencies, developing or confirming new theory and use as a confirmatory tool. Imminent congruence between the Eccles' Expectancy-Value Framework and the SATS-36 and some MPSP constructs, has also been by the highlighted.

5.2 Research Questions and Conclusions

This section responds to the research questions, hypotheses and provides a summary of findings as obtained in Chapter 4.Advancement of the knowledge and use of SEM and PLS in studying students' attitudes towards statistics' effect on their statistics outcomes is also highlighted. Recommendations to policy-makers and researchers are made.

Research Question 1:

Is there is a relationship between the perceptual and attitudinal constructs?

Conclusion 1:

To answer this question, the study considered the SAOM model by Ramirez *et al* (2012) which has been deemed congruent to EVM and The Theory of Planned behaviour for selecting variables for use in the study. The study identified the relationships between students' attitudes, their statistics self-efficacy and statistics outcome. The construct validity results have shown the difference in factor structures between the SAOM and SATS-36. From the twenty-three hypotheses tested, only fourteen were supported and are statistically significant owing to the t-values obtained. Construct, discriminant, convergent validity and reliability of the measures were also examined. Also, it has been established that fourteen of the twenty-three relationships are statistically significant based on the results of this study. These are listed below:

H1: There is positive relationship between Affect and Cognitive Competence is accepted. Feeling of affect may be due to the students' low cognitive competence.

H2: There is positive relationship between Difficulty and Cognitive Competence is accepted. This suggests that statistics subject difficulty may impact a students' cognitive competence.

H3: Interest is a positive predictor of Value, is accepted. It has been revealed that value attached to statistics subject is predicted by value.

H4: There is positive relationship between Affect and Interest is accepted. Affect has an impact on students' interest in the statistics subject.

H5: There is positive relationship between Cognitive Competence and Interest is accepted. This suggests that a students' cognitive competence affects the students' interest in statistics.

H6: There is positive relationship between Difficulty and Interest is accepted. The difficulty of the statistics subject impacts their interest in it.

H7: There is a positive relationship between Interest and Effort, is accepted. An interest in statistics subject by the students has an impact on the effort the put in.

H10: There is a relationship between Statistics Anxiety and Affect, is accepted. Statistics Anxiety is related to a students' affective domain.

H11: There is a relationship between Statistics Anxiety and Difficulty, is accepted. Difficulty of the subject makes students to develop anxiety towards statistics subject.

H15: There is relationship between Self-efficacy and Interest, is accepted. This means that students' interest in the statistics subject impacts their self-efficacy in statistics subject tasks.

H16: There is a relationship between Self-efficacy and Value, is accepted. It implies that students' self-efficacy impacts the value they attach to the statistics subject.

H19: There is significant and positive relationship between Self-Efficacy and Statistics Outcomes is accepted. This means that students' self-efficacy in statistics tasks have an impact on their statistics outcomes

H20: Value is a predictor of Statistics Outcomes, is accepted. This implies that students' statistics outcomes are predicted by the value they attach to it.

H21: Effort is a positive predictor of Statistics Outcomes, is accepted. This implies that students' outcomes are predicted by the effort they put in.

H23: There is positive relationship between Statistics Anxiety and Cognitive Competence is accepted. Students' statistics anxiety affects a students' cognitive competence.

According to theory and literature, all the constructs are related. These findings bring a new dimension to the students' attitudes research area, especially for the South African sample.

Research Question 2:

Is there a relationship between students' attitudes and their self-efficacy?

Conclusion 2:

The conclusions about indirect and total path coefficient effects are based on Tables 4.19 to 4.21. The results showed statistical significant relationship between two of the four self-efficacy constructs. The results showed that relationship between current statistics self-efficacy and statistics outcome measures and this is consistent with Bandura's (1996) claim as cited in (Finney & Schraw, 2003). This study highlights the fact that students with high self-efficacy may see the relevance of the subject in the degree programme of their choice.

Research Question 3:

Can Partial Least Squares analysis be used as a remedial tool to cure Structural Equation Modeling deficiencies?

Conclusion 3:

Tables 4.8 and 4.10 present the reliability results, and it is important to note that the PLS analysis reliability results are consistent with those of SEM with only two constructs in both valid. Due to how the two techniques differently compute the reliability statistics it may be wise to compare the SEM Cronbach's alpha with PLS analysis AVE instead. This paints a different picture, as there are five valid constructs as opposed to two. SEM uses the covariance matrix to compute model estimates, as compared to the variance matrix used for model estimation in PLS.

Research Question 4:

Can Partial Least Squares analysis be used as a confirmatory tool?

Conclusion 4:

Based on the conclusion three it is safe to assume that PLS has confirmatory properties. The AVE cut-off criterion suggests that 50 % of the variance should be explained by a construct for it to be declared valid**.** There is little or no evidence in literature at the time of compilation of this study on PLS being utilized as a confirmatory tool instead of CFA under SEM. The results revealed that not all of the hypotheses proposed were found to be statistically significant (Tables 4.16 through to 4.19), although the validity results were all positive (Table 4.14 and 4.15)

Research Question 5: Does Statistics Anxiety have a negative effect on a students' Statistics Outcome

Conclusion 5:

Regards to this question, it has been established according to the findings that there is virtually no effect of anxiety on statistics outcomes. This is in contradiction to the findings by Onwuegbuzie (2000 and 2004), Pan and Tang (2005), Keeley *et al* (2008), Macher *et al* (2011) Hamid and Sulaiman (2014) that statistics anxiety is a strong predictor of academic performance. It is important to note that a decrease in anxiety throughout a student's academic life has an impact in terms of the heightened perceived usefulness and statistics achievement.

Hypotheses results are presented in Table 4.17:

H1: There is positive relationship between Affect and Cognitive Competence is accepted. Feeling of affect may be due to the students' low cognitive competence.

H2: There is positive relationship between Difficulty and Cognitive Competence is accepted. This suggests that statistics subject difficulty may impact a students' cognitive competence.

H4: There is positive relationship between Affect and Interest is accepted. Affect has an impact on students' interest in the statistics subject.

H5: There is positive relationship between Cognitive Competence and Interest is accepted. This suggests that a students' cognitive competence affects the students' interest in statistics.

H6: There is positive relationship between Difficulty and Interest is accepted. The difficulty of the statistics subject impacts their interest in it.

H7: There is a positive relationship between Interest and Effort, is accepted. An interest in statistics subject by the students has an impact on the effort the put in.

H8: There is a relationship between Statistics Anxiety and Statistics Outcomes, is rejected. This means that students' statistics outcomes is not impacted by their statistics anxiety.

H20: Value is a predictor of Statistics Outcomes, is accepted. This implies that students' statistics outcomes are predicted by the value they attach to it.

H21: Effort is a positive predictor of Statistics Outcomes, is accepted. This implies that students' outcomes are predicted by the effort they put in.

H22: Cognitive Competence has positive relationship with Statistics Outcomes, is rejected. This means that students' cognitive competence has an impact on their statistics outcome.

H19: There is significant and positive relationship between Self-Efficacy and Statistics Outcomes is accepted. This means that students' self-efficacy in statistics tasks have an impact on their statistics outcomes

H9: There is a relationship between Statistics Anxiety and Effort, is rejected, suggesting that there is no relationship between Statistics Anxiety and Effort.

H10: There is a relationship between Statistics Anxiety and Affect, is accepted. Statistics Anxiety is related to a students' affective domain.

H11: There is a relationship between Statistics Anxiety and Difficulty, is accepted. Difficulty of the subject makes students to develop anxiety towards statistics subject.

H12: There is a relationship between Statistics Anxiety and Interest, is rejected. There is no relationship between students' feelings of anxiety and their interest in statistics subject.

H23: There is positive relationship between Statistics Anxiety and Cognitive Competence is accepted. Students' statistics anxiety affects a students' cognitive competence.

H13: There is a relationship between Difficulty and Self-efficacy, is rejected. This means that the difficulty of the statistics subject affect their self-efficacy in statistics tasks.

H14: There is a relationship between Effort and Self-efficacy, is rejected. Students' self-efficacy does not depend on the effort they put in.

H15: There is relationship between Self-efficacy and Interest, is accepted. This means that students' interest in the statistics subject impacts their self-efficacy in statistics subject tasks.

H16: There is a relationship between Self-efficacy and Value, is accepted. It implies that students' self-efficacy impacts the value they attach to the statistics subject.

H3: Interest is a positive predictor of Value, is accepted. It has been revealed that value attached to statistics subject is predicted by value.

H17: Value has a positive relationship with Effort, is rejected. This implies that effort put into the statistics subject does impact the value attached to it.

H18: Cognitive Competence has a positive relationship with Effort is rejected. This means that students' cognitive competence has no impact on the effort put in.

5.3 Recommendations

This section formulates recommendations to instructors, policy makers and researches for further studies taking the findings of this study into account.

5.3.1 Implications for Further Research

The current study was undertaken with undergraduate students enrolled in different sections of statistics courses in a public university in South Africa. Therefore, the results may not be generalized to the target population of the study outside the country and possibly to the world or other universities in the country. It is suggested that further studies should examine structural relationships in a nation-wide context; so that, the hypothesised relationships can be further generalised by extending the current study to different student populations in developing countries. In addition, it is suggested that further studies should conduct studies that make cross-cultural comparisons. Mvududu's (2003) study had participants drawn from Seattle Pacific University in the US and University of Zimbabwe. His study examined potential for attitudinal differences between the two groups, and found significant differences in statistics between these groups. He suggested that cross-cultural comparisons generate new insight into statistical pedagogy.

The current study also suggests further studies to use direct measures, such as mathematics and statistics tests and quizzes, for assessing students' self-efficacy and statistics outcome. This is consistent with Arumugam's (2014) findings that mathematics achievement and self-efficacy both have a positive significant relationship with statistics outcomes. In the current study, all the variables but students' statistics grades during taking and after statistics courses were measured only once. The study suggests that students' attitudes be monitored throughout the year. Therefore, the proposed relationships were static rather than longitudinal. It is suggested that further research should expand on the current study by using a longitudinal design in which the data are collected prior to, during, and after taking statistics courses. For example, Eccles and her colleagues (Eccles & Wigfield, 2002;

Wigfield & Eccles, 2000; 2002) suggested that individuals' performances and achievement choices influence their previous achievement-related experiences across time.

It is suggested that their proposal should be tested in a further study by extending the findings of the current study. Although, the current study revealed that the hypothesized "Statistics Attitudes-Outcomes Model" did not fit to the data well, it does not mean that this model is the best possible model. It is suggested that further research should investigate alternative models. The hypothesised and tested "Statistics Attitudes-Outcomes Model" of the current study was based on Eccles and her colleagues' application of expectancy value theory to mathematics education (Eccles & Wigfield, 1995, 2002; Wigfield & Eccles, 2000). The current study showed that the adaptation of Eccles' Model to the statistics education context was well explained by the data. Further studies could expand on the present findings by adapting "Statistics Attitudes-Outcomes Model" to different subject domains.

Due to the lack-of-good fit of the model to the data, it is suggested that further research be carried out to determine the effect of sample size, validity and reliability on model fit assessment indices. The study used ML and PLS estimation to calculate model estimates, and it thus suggests that further research be done using different estimation methods such as, the weighted least squares (WLS), full information maximum likelihood (FIML), and asymptotic distribution free method (ADF).

5.3.2 Implications Practice of Statistics Education

This study has demonstrated that the affective domain is important for explaining students' statistics outcomes. Therefore, this study suggests that students' attitudes should be given high priority when designing and implementing statistics curricula. It is highly important to suggest that students' positive attitudes toward statistics should be among the main goals of the statistics education; and accordingly, a statistics curriculum should involve various instructional practices, which enhance students' positive attitudes toward statistics.

It is also suggested that the effectiveness of the statistics curriculum should be evaluated by assessing students' attitudes toward statistics as well as by assessing short term and long-term outcomes. Accordingly, it is suggested that statistics instructors in universities should be informed and trained about the importance of their students' attitudes and how to implement and evaluate the instruction in a way aimed at enhance students' positive attitudes. It is also suggested for instructors to employ statistics activities that are interesting, enjoyable and fun for students to participate which would help students to have more interest and positive affect toward statistics (Berk & Nanda, 1998; Lesser & Pearl, 2008; Milburn, 2007).

The study further suggests that instructors for statistics courses be weary of their students' perceptions about their capabilities in statistics and deliver the instruction appropriately to the level of students. In addition, revealing the importance of attitudes toward statistics, the current study suggests that students' attitudes toward statistics are as necessary as students' achievement in statistics. Overall, the current study demonstrated that students' attitudes toward statistics played an important role in for explaining students' statistics outcomes. Several studies have suggested that instructional interventions such as technology use (Suanpang *et al*., 2004; Wiberg, 2009) increased students' positive attitudes toward statistics. Therefore, in sum, it is suggested to statistics teachers to adopt appropriate instructional methods to increase positive attitudes toward statistics, for example, introducing students to basic statistical software from which they can capture, organise, analyse and interpret the data.

5.4 Scope Limitations and Delimitations of the Study

The following are limitations and delimitations of the study:

5.4.1 Limitations

The study has used only primary data collected by administering the questionnaires to students registered for a course in Statistics. The study has been limited to students registered for first year modules in statistics at the North-West University, Mafikeng Campus. The study conducted over a certain interval of time is a snapshot dependent on conditions occurring during that time. An example would be general change of attitudes throughout a student's academic life based on previous and present experiences. Extra care was taken as to ensure that the limitations as stated do not affect the study negatively and results in bias.

Students taking introductory statistics courses usually complete it after two or three attempts, i.e. in the second year or third year of their studies. These students have been seen to underachieve more in this course than their second-year and third-year counterparts; who by virtue of being registered at that level may show little or no sign of misperceptions or negative attitudes toward statistics, i.e. second and third-year students might respond differently or positively to some items due to their having succeeded in the course before, and that would bring about another dimension (which we are not interested in for the moment) to this study. The use of very old sources by the study is noted, as these form the basis for the SEM and PLS theoretical frameworks.

5.4.2 Delimitations

Delimitation for this study would be the exclusion of respondents who are taking second level or second year statistics courses as they are also undergraduate students. Care was taken during administration of the questionnaires and capturing of the data that possible omissions of information by the respondent or data-capturer be as minimal as possible to reduce missing data. The selected methodology and variables in the study also set a boundary on what the findings can ascertain. This was done with aim to respond to outlined objectives and hypotheses only, by determining latent variables that need instructors' attention and possible intervention by the faculty in question.

5.5 Summary

This study applied two multivariate techniques to analyse the hypothesised structural model and to determine attitudinal relationships. The secondary objective was to determine a model with best fit and the possible use of PLS as remedial and confirmatory tool and to test the set hypotheses. In general, two of the suggested SAOM constructs were not confirmed. In the main, the study explored the applicability of SEM to the hypothesised Statistics Attitudes-Outcomes Model. An EFA revealed that there are nine constructs in the structural model. The relationship of self-efficacy on statistics outcome was confirmed. Due to how the two techniques, SEM and PLS, differently compute the reliability statistics it may be wise to compare the structural equation modeling Cronbach's alpha with PLS analysis average variance extracted instead. This paints a different picture, as there are five valid constructs as opposed to two. It is safe to assume that PLS has confirmatory properties. The results revealed that not all of the hypotheses proposed were found to be statistically significant, although the validity results were all positive. Contradictions of study findings with other literature were noted and assessed. Further methodological research is suggested to determine the effect of sample size, number of constructs and observed variables on the fit of the model.

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Appendices

Appendix A: Questionnaire

PLEASE READ:

Dear Respondent

You are invited to participate in an academic research study conducted by Bokang Ncube, a Masters student from the Department of Statistics at the North West University.

Please note the following:

This study involves an anonymous survey. Your name will not appear on the questionnaire and the answers you give will be treated as strictly confidential. You cannot be identified in person based on the answers you give. Please be advised that the information you provide herein will only be communicated the management of the faculty and of NWU.

- Your participation in this study is very important to us. You may, however, choose not to participate and you may also stop participating at any time without any negative consequences.
- Please answer the questions in the attached questionnaire as completely and honestly as possible. This should not take more than 7-10min minutes of your time
- The results of the study will be used for academic purposes only and may be published in an academic journal. We will provide you with a summary of our findings on request.
- Please contact my supervisor, Dr. Moroke on Ntebo.Moroke@nwu.ac.za if you have any questions or comments regarding the study.

Please sign the form to indicate that:

- You have read and understood the information provided above.
- You give your consent to participate in the study on a voluntary basis.

____

Signature

Survey of Attitude toward Statistics

DIRECTIONS: The statements are designed to identify your attitudes and perception about statistics. Each item has 7 possible responses. The responses range from 1 (strongly disagree) through 4 (neither disagree nor agree) to 7 (strongly agree). Please read each statement. Mark the one response. Record your answer and move quickly to the next item. Please respond to all of the statements. Circle your selection.

SECTION 1: ATTITUDES ABOUT STATISTICS

1 Strongly disagree	2 Disagree	3 Somewhat disagree	4 Neither disagree nor agree	5 Somewhat agree	6 Agree	7 Strongly agree

Directions

I like statistics.	1	2	3	4	5	6	7
I feel insecure when I have to do statistics problems.	1	2	3	4	5	6	7
I have trouble understanding statistics because of how I think.	1	2	3	4	5	6	7
Statistics formulas are easy to understand.	1	2	3	4	5	6	7
Statistics is worthless.	1	2	3	4	5	6	7
Statistics is a complicated module.	1	2	3	4	5	6	7
Statistics should be a required part of my professional training.	1	2	3	4	5	6	7
Statistical skills will make me more employable.	1	2	3	4	5	6	7
I have no idea of what's going on in this statistics course.	1	2	3	4	5	6	7
Statistics is not useful to the profession of my choice.	1	2	3	4	5	6	7
I get frustrated going over statistics tests in class.	1	2	3	4	5	6	7
Statistical thinking is not applicable in my life, outside my job.	1	2	3	4	5	6	7
I use statistics in my everyday life	1	2	3	4	5	6	7
I am under stress during statistics class.	1	2	3	4	5	6	7
I enjoy taking statistics modules.	1	2	3	4	5	6	7
Statistics conclusions are rarely presented in everyday life.	1	2	3	4	5	6	7
Statistics is a subject quickly learned by most people.	1	2	3	4	5	6	7
Learning statistics requires a great deal of discipline.	1	2	3	4	5	6	7
I will have no application for statistics in my profession.	1	2	3	4	5	6	7
I make a lot of mathematical errors in statistics.	1	2	3	4	5	6	7
I am scared by statistics.	1	2	3	4	5	6	7
Statistics involves massive computations.	1	2	3	4	5	6	7
I am motivated to learn statistics.	1	2	3	4	5	6	7
I understand statistics equations.	1	2	3	4	5	6	7
Statistics is irrelevant in my life.	1	2	3	4	5	6	7
Statistics is highly technical.	1	2	3	4	5	6	7
I find it difficult to understand statistical concepts.	1	2	3	4	5	6	7
Most people have to learn a new way of thinking to do statistics.	1	2	3	4	5	6	7
I would deregister statistics anytime.	1	2	3	4	5	6	7
I try to complete all of my statistics assignments.	1	2	3	4	5	6	7
I work hard in my statistics module.	1	2	3	4	5	6	7
I try to study hard for every statistics test.	1	2	3	4	5	6	7
I try to attend every statistics class session.	1	2	3	4	5	6	7
I am interested in being able to communicate statistical information to others.	1	2	3	4	5	6	7
I am interested in using statistics.	1	2	3	4	5	6	7
I am interested in understanding statistical concepts.	1	2	3	4	5	6	7
I am interested in learning statistics.	1	2	3	4	5	6	7
I do not want to learn to like statistics and anything that has got to do with it.	1	2	3	4	5	6	7
If you could, how likely is it that you would choose to take another module in statistics?	1	2	3	4	5	6	7
I feel anxious when taking a statistics test or examination.	1	2	3	4	5	6	7
I feel anxious when interpreting statistical results to a friend or the lecturer.	1	2	3	4	5	6	7

SECTION 2: PERCEPTIONS ABOUT STATISTICS

NOTICE that the labels for the scale on each of the following items **DIFFER** from those used above

How good at mathematics are you?	1	2	3	4	5	6	7
In the field in which you hope to be employed when you finish school, how much will you use statistics?	1	2	3	4	5	6	7
How confident are you that you have mastered introductory statistics material up to this point in the present academic year?	1	2	3	4	5	6	7
As you complete the remainder of your degree program, how much will you use statistics?	1	2	3	4	5	6	7
I am doing well in my statistics module.	1	2	3	4	5	6	7
Statistics is relatively easy.	1	2	3	4	5	6	7
A thought of statistics makes me very nervous.	1	2	3	4	5	6	7
I do not enjoy statistics, since I have never enjoyed mathematics.	1	2	3	4	5	6	7
I believe statistics is not really bad. It is just too mathematical.	1	2	3	4	5	6	7
I need strong mathematics background to do well in statistic	1	2	3	4	5	6	7
Statistics is very different from mathematics	1	2	3	4	5	6	7
Can identify the scale of measurement for a variable.	1	2	3	4	5	6	7
Can identify if a distribution is skewed.	1	2	3	4	5	6	7
Can select the correct statistical procedure to be used to answer a question.	1	2	3	4	5	6	7
Can communicate statistical results without any problem	1	2	3	4	5	6	7
Can read a value from any statistical table.	1	2	3	4	5	6	7

ADDITIONAL INFORMATION

What program are you enrolled for at the university? ______________________________

MARK ONE best response.

Last semester I obtained:

1. 75% - 100% 2. 50% - 74% 3. 0 – 49% 4. I did not write/qualify

Do you know definitely what grade you will receive in this course?

1. Yes ☐ 2. No ☐

What grade do you expect to receive in this course?

1. 75% - 100% 2. 50% - 74% 3. 0 – 49% 4. I do not think I will pass this semester

Gender

1. Male ☐ 2. Female ☐

The following statements require you to **WRITE** a little **DESCRIPTION**.

1.What do you believe could be done differently to help you understand statistics?

____

2. In general, my statistics class is____

Appendix B: Tables of Results
Table A: Initial CFA Results

Standardized Results for Covariances Among Exogenous Variables					
Var1	**Var2**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
F1	**F2**	cf1f2	-0.18695	0.06341	-2.94838
F1	**F3**	cf1f3	-1.00496	0.02823	-35.59722
F1	**F4**	cf1f4	-0.36531	0.05081	-7.19031
F1	**F5**	cf1f5	0.83248	0.03783	22.00629
F1	**F6**	cf1f6	-0.13936	0.05664	-2.46038
F1	**F7**	cf1f7	-0.34342	0.05139	-6.68299
F1	**F8**	cf1f8	-0.29320	0.05551	-5.28187
F3	**F2**	cf3f2	0.02276	0.05774	0.39409
F4	**F2**	cf4f2	0.25695	0.05156	4.98304
F5	**F2**	cf5f2	-0.49838	0.05018	-9.93095
F6	**F2**	cf6f2	0.25606	0.05308	4.82363
F7	**F2**	cf7f2	0.25451	0.05161	4.93092
F8	**F2**	cf8f2	0.25612	0.05439	4.70884
F4	**F3**	cf4f3	0.34664	0.04504	7.69564
F5	**F3**	cf5f3	-0.68817	0.03650	-18.85360
F6	**F3**	cf6f3	0.07772	0.05102	1.52332
F7	**F3**	cf7f3	0.28767	0.04655	6.17923
F8	**F3**	cf8f3	0.25895	0.04979	5.20086
F5	**F4**	cf5f4	-0.44830	0.04323	-10.37118
F6	**F4**	cf6f4	0.42784	0.04058	10.54324
F7	**F4**	cf7f4	0.42430	0.03937	10.77837
F6	**F5**	cf6f5	-0.13592	0.05190	-2.61863
F7	**F5**	cf7f5	-0.25981	0.04854	-5.35300
F8	**F5**	cf8f5	-0.36774	0.04859	-7.56803
F7	**F6**	cf7f6	0.21201	0.04619	4.59033
F8	**F6**	cf8f6	0.24907	0.04799	5.19008
F8	**F7**	cvf8f7	0.57322	0.03616	15.85185
F8	**F4**	_Add1	0.55704	0.03687	15.10667

Table B: Results of model ML6

Standardized Results for Covariances Among Exogenous Variables					
Var1	**Var2**	**Parameter**	**Estimate**	**Standard Error**	**t Value**
F1	**F2**	cf1f2	-0.20701	0.05301	-3.90498
F1	**F3**	cf1f3	-0.28469	0.05154	-5.52348
F1	**F4**	cf1f4	-0.15200	0.05623	-2.70350
F1	**F5**	cf1f5	-0.02477	0.06602	-0.37519
F1	**F6**	cf1f6	-0.30883	0.05425	-5.69303
F1	**F7**	cf1f7	0.52659	0.04540	11.59950
F1	**F8**	cf1f8	-0.18992	0.05647	-3.36335
F1	**F9**	cf1f9	0.75588	0.04213	17.94070
F2	**F3**	cf3f2	0.39005	0.04618	8.44621
F2	**F4**	cf4f2	0.28480	0.05144	5.53686
F2	**F5**	cf5f2	0.26388	0.06070	4.34710
F2	**F6**	cf6f2	0.61556	0.03914	15.72836
F2	**F7**	cf7f2	-0.19892	0.05359	-3.71172
F2	**F8**	cf8f2	0.56988	0.04161	13.69490
F2	**F9**	cf9f2	-0.13276	0.06196	-2.14271
F3	**F4**	cf4f3	0.44839	0.04623	9.70013
F3	**F5**	cf5f3	0.27775	0.06075	4.57224
F3	**F6**	cf6f3	0.67335	0.03616	18.62111
F3	**F7**	cf7f3	-0.16939	0.05438	-3.11493
F3	**F8**	cf8f3	0.59010	0.04094	14.41213
F3	**F9**	cf9f3	-0.33100	0.05837	-5.67055
F4	**F5**	cf5f4	0.34002	0.06149	5.52941
F4	**F6**	cf6f4	0.38563	0.05205	7.40845
F4	**F7**	cf7f4	0.01734	0.05763	0.30096
F4	**F8**	cf8f4	0.30765	0.05408	5.68826
F4	**F9**	cf9f4	-0.15947	0.06424	-2.48246
F5	**F6**	cf6f5	0.39952	0.06128	6.52015
F5	**F7**	cf7f5	0.29999	0.06288	4.77123
F5	**F8**	cf8f5	0.21628	0.06530	3.31236
F5	**F9**	cf9f5	-0.27545	0.07239	-3.80516
F6	**F7**	cf7f6	-0.18274	0.05752	-3.17709
F6	**F8**	cf8f6	0.68678	0.03947	17.39864
F6	**F9**	cf9f6	-0.32667	0.06234	-5.24014
F7	**F8**	cff8f7	-0.23162	0.05616	-4.12452
F7	**F9**	cf9f7	0.30971	0.06160	5.02774
F8	**F9**	cf9f8	-0.26464	0.06334	-4.17829

TABLE C: Items on the Statistics-Outcomes Model

Constructs	Labels	Indicators
Affect	Af_1	I like learning about statistics
	Af_2	I feel insecure when I have to solve statistics problems
	Af_3	I get frustrated with my statistics tests results
	Af_4	I am under stress during statistics class
	Af_5	I enjoy taking statistics courses
	Af_6	I am scared by statistics
	Af_7	I would deregister statistics anytime
	Af_8	I feel anxious when taking a statistics test or examination*
	Af_9	I feel anxious when interpreting statistical results to a friend or the lecturer*
Cognitive Competence	CC_1	I have trouble understanding statistics because of the way I think
	CC_2	I have no idea of what is going on in this statistics course
	CC_3	I make a lot of mathematical errors in statistics
	CC_4	I can understand most of the statistical ideas
	CC_5	I understand equations related to statistics
	CC_6	I find it difficult to understand statistical concepts
Value	V_1	Statistics is not useful in my daily routine
	V_2	Statistics is required in my professional training
	V_3	Statistical skills will make me more employable
	V_4	Statistics is not useful at the workplace
	V_5	Statistical thinking is not applicable outside my career/profession
	V_6	Use statistics in my everyday life
	V_7	Statistics knowledge are rarely applied in daily life
	V_8	I have no application for statistics in my future profession
	V_9	Statistics is irrelevant in my life
Difficulty	D_1	Statistics formulas are easy to understand
	D_2	Statistics is a complicated subject
	D_3	Statistics is a subject quickly learned by most people
	D_4	Learning statistics requires a great deal of discipline
	D_5	Statistics involves massive computations
	D_6	Statistics involves massive computations
	D_7	Most people have to learn a new way of thinking to do statistics
Interest	I_1	I am interested in being able to communicate statistical information to others
	I_2	I am interested in using statistics

	I_3	I am interested in understanding statistical information
	I_4	I am interested in learning statistics
	I_5	I do not want to learn to like statistics*
Effort	E_1	I plan to complete all of my statistics assignments
	E_2	I plan to work hard in my statistics course
	E_3	I plan to study hard for every statistics test
	E_4	I plan to attend every statistics class session
Self-Efficacy	SE_1	Can identify the scale of measurement for a variable
	SE_2	Can identify if a distribution is skewed.
	SE_3	Can select the correct statistical procedure to be used to answer a question
	SE_4	Can communicate statistical results without any problem
	SE_5	Can read a value from any statistical table.
	SE_6	I am confident that I have mastered introductory statistics material up to this point in the present academic year
Statistics Outcome	SO_1	If I could, I would choose to take another statistics module
	SO_2	In the field in which I hope to be employed when I finish school, I will use statistics
	SO_3	As I complete the remainder of my degree program,I will often use statistics

*** Added items**

Appendix C: Consent Letter

NORTH-WEST UNIVERSITY
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ETHICS APPROVAL CERTIFICATE OF PROJECT

Based on approval by the **Human Resource Research Ethics Committee, Mafikeng Campus**, the North-West University Institutional Research Ethics Regulatory Committee (NWU-IRERC) hereby approves your project as indicated below. This implies that the NWU-IRERC grants its permission that, provided the special conditions specified below are met and pending any other authorisation that may be necessary, the project may be initiated, using the ethics number below.

Project title: Structural equation modelling applied to proposed statistics attitudes-outcomes model: A case of North-West University statistics students.

Project Leader: **Prof ND Moroke**
Student: **BA Ncube**

Ethics number:	N	W	U	-	0	0	1	5	2	-	1	6	-	A	9
	Institution				Project Number						Year			Status	

Status: S = Submission; R = Re-Submission; P = Provisional Authorisation; A = Authorisation

Approval date: 2016-02-22 Expiry date: 2019-02-22 Category N/A

Special conditions of the approval (if any): None

General conditions:

While this ethics approval is subject to all declarations, undertakings and agreements incorporated and signed in the application form, please note the following:

- *The project leader (principle investigator) must report in the prescribed format to the NWU-IRERC:*
  - *annually (or as otherwise requested) on the progress of the project,*
  - *without any delay in case of any adverse event (or any matter that interrupts sound ethical principles) during the course of the project.*
- *The approval applies strictly to the protocol as stipulated in the application form. Would any changes to the protocol be deemed necessary during the course of the project, the project leader must apply for approval of these changes at the NWU-RERC. Would there be deviated from the project protocol without the necessary approval of such changes, the ethics approval is immediately and automatically forfeited.*
- *The date of approval indicates the first date that the project may be started. Would the project have to continue after the expiry date, a new application must be made to the NWU-IRERC and new approval received before or on the expiry date.*
- *In the interest of ethical responsibility the NWU-IRERC retains the right to:*
  - *request access to any information or data at any time during the course or after completion of the project;*
  - *withdraw or postpone approval if:*
    - *any unethical principles or practices of the project are revealed or suspected,*
    - *it becomes apparent that any relevant information was withheld from the NWU-IRERC or that information has been false or misrepresented,*
    - *the required annual report and reporting of adverse events was not done timely and accurately,*
    - *new institutional rules, national legislation or international conventions deem it necessary.*

The IRERC would like to remain at your service as scientist and researcher, and wishes you well with your project. Please do not hesitate to contact the IRERC for any further enquiries or requests for assistance.

Yours sincerely

Linda du Plessis

Prof Linda du Plessis
Chair NWU Institutional Research Ethics Regulatory Committee (IRERC)