Examining the Relationships among Mathematics Achievement, Attitudes toward Statistics, and Statistics Outcomes: Application of Structural Equation Modeling

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This is to certify that the thesis prepared by Zelalem Firisa, entitled: *Examining the Relationships among Mathematics Achievement, Attitudes toward Statistics, and Statistics Outcomes: Application of Structural Equation Modeling* and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Statistics (Applied Statistics) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Abstract

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Statistics courses have become an essential part of many programs in higher education. Thus, students from a broad spectrum of disciplines take statistics courses in higher education. Structural equation modeling can be defined as a class of methodologies that seeks to represent hypotheses about the means, variances, and covariances of observed data in terms of a smaller number of 'structural' parameters defined by a hypothesized underlying conceptual or theoretical model. The main objective of this study is to investigate the structural relationships among mathematics achievement, attitudes toward statistics, and statistics outcomes by testing a structural model, called "Statistics Attitudes-Outcomes Model". In the current study, a survey design was adopted and a questionnaire was used to gather information from 205 undergraduate statistics non-major Addis Ababa University students who registered for introductory statistics courses offered by the Department of Statistics in the first semester of the 2013/14 Academic Year. The hypothesized model was tested by Structural Equation Modeling (SEM) technique using Smart PLS 2.0 statistical software. Participants of this study generally reported positive attitudes toward statistics except that they perceived the difficulty of statistics as neutral and they were indifferent in terms of their individual affection to statistics. Mathematics achievement variable had medium total standardized effects on statistics outcomes variable; however, effort and interest variables had small total effects on explaining statistics outcomes, and difficulty had non-significant total effect on explaining statistics outcomes. The results indicated that, students' past and overall mathematics achievement, interest in statistics and the effort they expand to learn statistics were found as important factors for explaining their statistics outcomes.

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CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Statistics is defined as "the science of conducting studies to collect, organize, summarize, analyze, and draw conclusions from data" (Bluman, 2012). It is obvious that statistics is in our everyday lives. It is on internet, newspapers, television, and everywhere. The reports of political elections, sports games, advertisements, census records, weather forecasts, and many situations, which we come across every day, use basic statistics knowledge. Statistics is about solving real world problems. Therefore, it is not only needed for conducting scientific research but also needed for being informed citizen, and for advancing in technology as a society (Hand, 1998).

Statistics courses have become an essential part of many programs in higher education. The rationale for teaching statistics at the college level is to enable students to handle, use, and interpret research or statistical data in their field of study. An additional goal of teaching statistics is to prepare students to deal effectively with statistical aspects of the world outside the classroom (Nasser, 2004). In the current study, a statistics course refers to the introductory course offered to undergraduate students who are not majoring in statistics.

Statistics is an important tool for any individual in today's world in which numerical data are increasingly presented (Ben-Zvi & Garfield, 2010). Accordingly, students from a broad spectrum of disciplines take statistics courses in higher education. We believe that, in order for students to succeed and to use statistics, they should think that statistics is valuable in their lives. We also believe that it is important for students to like statistics, believe that they can understand and use statistics, and think that statistics is not too difficult. In other words, it is important for students to have positive attitudes toward statistics (Schau, 2003). Based on others' definitions of attitudes (Ajzen, 2005), we define attitudes toward statistics as a multidimensional construct representing students' learned predispositions to respond positively or negatively to statistics.

Students pursuing a degree are usually requested to enroll in introductory statistics courses at the beginning of their degree program. In some cases, students only have access to the next courses of their degree program once they have passed an introductory statistics examination, and/or their final dissertations often require the use of statistics. Unfortunately, many students find it difficult to grasp statistical concepts, thus, they have problems with dealing with this discipline, and they attain low levels of performance. Despite their efforts, instructors of introductory statistics courses that are aimed at preparing students to understand, handle, and make use of research data in their field of study, often fail to achieve this (Chiesi and Primi, 2010).

While statistics educators have focused on improving the cognitive side of instruction, that is, the skills and knowledge that students are expected to develop, little regard has been given to non-cognitive issues such as students' feelings, attitudes, beliefs, interests, expectations, and motivations (Gal and Ginsburg, 1994).

Nonetheless, results of these studies revealed a positive contribution of mathematics achievement on statistics achievement (Johnson and Kuennen, 2006; Lalonde and Gardner, 1993; Nasser, 2004) and interventions such as technology use (delMas et al., 1999) and use of real-life examples enhanced cognitive learning outcomes in statistics (Evans, 2007). Besides the research that focused on the cognitive side of statistics education, a limited number of studies were conducted on understanding students' attitudes toward statistics and most of these studies adopted survey designs and indicated that positive attitudes toward statistics contribute to the success in statistics courses (Emmioglu, 2011, Dempster and McCorry, 2009; Evans, 2007; Tempelaar et al., 2007).

In addition to the above results, researchers also argued that students' attitudes toward statistics are important factors for influencing teaching-learning process and students' statistical behavior after they leave the classroom, and for influencing their choice of enrolling in a new statistics course (Garfield et al., 2002; Schau, 2003). On the other hand, a limited number of experimental studies were conducted and revealed that interventions such as technology use (Carlson and Winquist, 2011; Suanpang et al., 2004; Wiberg, 2009) increased students' positive attitudes toward statistics.

Structural equation modeling can be defined as a class of methodologies that seeks to represent hypotheses about the means, variances, and covariances of observed data in terms of a smaller number of ‘structural’ parameters defined by a hypothesized underlying conceptual or theoretical model. Historically, structural equation modeling derived from the hybrid of two separate statistical traditions. The first tradition is factor analysis developed in the disciplines of psychology and psychometrics. The second tradition is simultaneous equation modeling developed mainly in econometrics, but having an early history in the field of genetics and introduced to the field of sociology under the name *path analysis* (Kaplan, 2001). Structural equation modeling (SEM) first appeared in the marketing literature in the early 1980s (Fornell and Larcker 1981), but in recent years, its application has become quite widespread.

1.2 Statement of the Problem

Students who take statistics courses from a variety of social and natural sciences disciplines are expected to be equipped with the statistical skills and to be motivated to use statistics at the end of their education. However, Statistics educators routinely mention that many students enter statistics courses with negative views or later develop negative feelings about the domain of statistics (Perney and Ravid, 1991; Peterson, 1991). Perney and Ravid (1991) describe a scenario: "Statistics courses are viewed by most college students as an obstacle standing in the way of attaining their desired degree. It is not uncommon to see students who delay taking the statistics courses until just before graduation…College professors who teach the research and statistics course are all too familiar with the high level of anxiety exhibited by the students on the first day of the term." On the other hand, Peterson (1991) wrote about introductory statistics courses in Science News as: "Few college students escape taking an introductory course in statistics. But for many of these students, the lessons don't seem to stick. They remember the pain but not the substance. `Such initial courses tend to turn students off,' says Barbara A. Bailar, executive director of the American Statistical Association." The existing literatures also demonstrate that some of the students even call statistics as “sadistics” (Lalonde and Gardner, 1993). Hence, several studies recommend that statistics courses need to be revised in a way to motivate students to learn statistics (Carnell, 2008; Dempster and McCorry, 2009; Wiberg, 2009). Thus, it is essential to carry out more research to understand the role of attitudes in statistics education. By going this way, it might be possible to find out why students have certain attitudes toward statistics and to suggest ways to increase students’ positive attitudes toward statistics. Eventually, the quality of statistics education would improve with the help of such studies (Garfield, et al., 2002).

Literatures indicate that few attempts have been made to understand students' attitudes toward statistics but several shortcomings were apparent in most early studies. Firstly, most of these studies were based on experiences of researchers, instead of educational and cognitive models (Evans, 2007; Wiberg, 2009). Secondly, there have been strong inconsistencies with the use of instruments measuring attitudes toward statistics and most of the existing instruments were widely criticized in terms of their internal structures (Emmioglu, 2011). Lastly, most of these studies have focused on a small part of relationships between attitudes and achievement but have not investigated the complex or structural relationships (Dempster and McCorry, 2009). Nevertheless, this study will have some characteristics, which will contribute to the present literature and the practice of teaching statistics by attempting to improve some of the shortcomings mentioned above.

1.3 Objectives of the Study

1.3.1 General Objective

The general objective of this study is to investigate the structural relationships among mathematics achievement, attitudes toward statistics, and statistics outcomes by testing a structural model called "Statistics Attitudes-Outcomes Model".

1.3.2 Specific Objectives

The specific objectives of the study are:

- To describe participants' characteristics in terms of their mathematics achievement, expectancy of statistics success, willingness to use statistics, and attitudes toward statistics
- To make preliminary judgments on complex relationships among study constructs using correlational techniques
- To examine whether students in different class levels had different levels of attitudes toward statistics
- To make relevant recommendations for the practice of statistics education and for future researchers

The conceptual structure of the proposed “Statistics Attitudes-Outcomes Model” (Emmiouglu, 2011) is presented below:

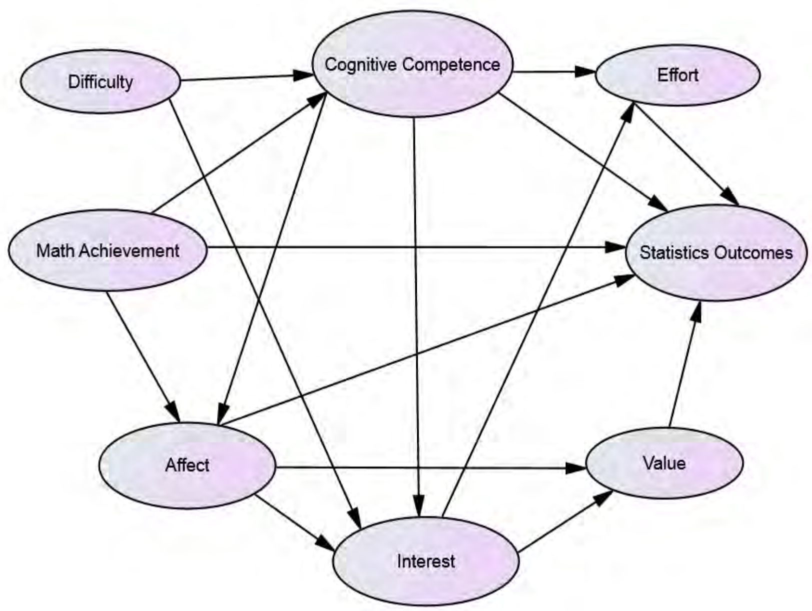

Figure 1.1: Conceptual Structure of the “Statistics Attitudes-Outcomes Model”

1.4 Significance of the Study

- It is expected that the current study would contribute to the literature by using a current and widely recognized instrument Survey of Attitudes Toward Statistics-36© (SATS-36©), to assess students’ attitudes toward statistics (Tempelaar et al., 2007).
- The current study makes an essential contribution to the literature as statistics outcomes variable include students’ willingness to use statistics in the remainder of degree program and willingness to use statistics when employed but not statistics achievement because researchers demonstrate attitudes as important factors for influencing students’ statistical behavior after they leave the classroom (Garfield et al., 2002; Schau, 2003).
- Last but not the least, this study would contribute to the Ethiopian literature and to the

practice of statistics education in Ethiopia. Additionally, as there are no research studies on statistics education in Ethiopia, the results of the study would suggest new directions for future studies.

1.5 Limitations of the Study

- In the current study, attitudes toward statistics, self-reported mathematics achievement, and statistics outcomes variables were self-reports of the participants. Therefore, the scope of the data collected in this study is limited to the participants' perceived levels of related constructs.
- The results of the current study are limited to the participants of the study who were enrolled in introductory statistics courses.
- The proposed relationships in "Statistics Attitudes-Outcomes Model" are limited to the single point in time rather than inferring causal relationships by a longitudinal or an experimental design, as in the current study, all of the variables were measured at a single point in time.

1.6 Definition of Terms

Cognitive Competence is defined as students' perceptions about their intellectual knowledge and skills when applied to statistics along with their expectancies for success in statistics (Schau, 2005).

Attitudes toward Statistics are defined as individuals' learned positive or negative responses with respect to statistics. In the present study, this broad construct consists of six components: affect, value, cognitive competence, interest, difficulty, and effort. Accordingly, individuals with positive attitudes toward statistics are assumed to have positive feelings toward statistics. They value statistics and they have cognitive competence and interest in statistics. They perceive statistics as a subject that is not difficult and they spend effort to do well in statistics (Schau, 2003).

Affect is defined as students' positive and negative feelings concerning statistics (Schau, 2005).

Value is defined as students' attitudes about the usefulness, relevance, and worth of statistics in personal and professional life (Schau, 2005).

Difficulty is defined as students' attitudes about the difficulty of statistics as a subject (Schau, 2005).

Effort is defined as the amounts of work students spend to learn statistics (Schau, 2005).

Interest is defined as students' level of individual interest in statistics (Schau, 2005).

Mathematics Achievement is defined, in this study, as the evidence of self reported previous and overall mathematics achievement (Emmioglu, 2011).

Statistics Outcomes are defined, in this study, as the students' future use of statistics (Emmioglu, 2011). In the current study, statistics outcomes involve two components: willingness to use statistics in the remainder of the degree program, and willingness to use statistics when employed.

CHAPTER TWO

LITERATURE REVIEW

Several studies have investigated the role of attitudes on explaining statistics outcomes using Structural Equation Modeling technique. These studies focused on several attitudes and statistics outcomes variables (Lalonde and Gardner, 1993; Onwuegbuzie, 2003; Nasser, 2004; Tempelaar et al., 2007; Dempster and McCorry 2009; Chiesi and Primi, 2010; Emmioglu, 2011). We first present a detailed overview of the results of these previous studies concerning structural equation modeling and emphasize the most important findings and trends that can be formulated based on these results.

Literatures demonstrate that, the first statistics attitude-achievement model called Gardner's "Socio-Educational Model" was developed and studied by Lalonde and Gardner (1993). They collected data from 91 (19 males and 72 females) psychology students in Canada from two sections of an introductory statistics course that spanned two semesters. They conceptualized the learning of statistics as analogous to the learning of a second language. Accordingly, they based their structural model on a theory of language learning. Their results indicated that Situational Anxiety had no significant effect on Achievement. Their final model had Mathematical Aptitude as a negative predictor of Situational Anxiety and a positive cause of Achievement, Situational Anxiety as a negative influence on an individual's Attitude-Motivation Index which in turn had a positive effect on Effort which leads to Achievement. They reported a statistically significant impact of mathematical aptitude, attitudes toward statistics, and effort on students' statistics achievement.

After a decade, Onwuegbuzie (2003) developed a similar model to Gardner based on foreign language learning theory for predicting statistics achievement. He collected data from a sample comprised 130 graduate students from a number of education disciplines (early childhood education, elementary education, secondary education, special education, and psychology) who had enrolled in three sections of an introductory-level, quantitative-based educational research course at a southeastern university. Onwuegbuzie administered four instruments to collect the data: the Statistical Anxiety Rating Scale (SARS), the Research Anxiety Rating Scale (RARS), the Study

Habits Inventory (SHI), and the Background Demographic Form (BDF). Generally, he reported that statistics anxiety and achievement expectation played a central role in the model, mediating the relationship between statistics achievement and the variables: research anxiety, study habits, course load, and the number of statistics courses taken.

A year later, Nasser (2004) collected complete data from 162 Arabic speaking pre-service teachers enrolled in a teacher-training program for elementary and middle schools in an academic institution in Israel. She used the Arabic version of Survey of Attitudes toward Statistics (SATS) to assess attitudes toward statistics and the Arabic version of Mathematics Attitude Scale (MAS) to measure attitudes toward mathematics. In terms of the correlation between constructs, Nasser reported moderate and statistically significant correlation among statistics achievement and mathematical aptitude, attitudes towards mathematics, the cognitive component of attitudes toward statistics, learning anxiety and lack of computation self-concept. Testing the structural relationships among the constructs, she reported statistically significant direct effects from mathematics aptitude (measured by the number of high school mathematics units studied by students and by students' high school mathematics grades) and attitudes toward statistics to statistics achievement.

Besides the previously mentioned theories, expectancy value theory has inspired researchers for examining students' attitudes toward statistics. Tempelaar, et al. (2007) investigated the impact of statistics attitudes on statistics achievement and statistical reasoning abilities by estimating a structural equation model based on Eccles and colleagues' application of expectancy value model of achievement motivation. They used Survey of Attitudes toward Statistics-36© (SATS-36©) and Statistical Reasoning Abilities (SRA) to collect data from business (sample size = 842) and economics students (sample size = 776) of the Maastricht University found in the Netherlands. In terms of student's attitudes toward statistics, they reported that students had positive attitudes toward statistics for Affect, Cognitive Competence, Value, Interest, and Effort variables. They have used the method of Covariance Based Structural Equation Modeling (CB-SEM) in order to estimate the parameters of their model using LISREL statistical software. They reported statistically significant impact of effort, value, difficulty, and interest on statistical reasoning and a statistically significant impact of cognitive competence, difficulty, and effort on performance in statistics.

In 2009, Dempster and McCorry administered the Survey of Attitudes Toward Statistics-28© (SATS-28©) and collect data from 154 undergraduate psychology programme students at their first statistics class in the United Kingdom to study the role of previous experience and attitudes toward statistics in statistics assessment outcomes among undergraduate psychology students. Assessing the correlations among the constructs, they reported that attitudes about cognitive competence, affect and value are most strongly related to performance on the statistics assessment and that affect is strongly related to cognitive competence. Their correlational studies also revealed that students' statistics achievement was significantly related to their attitudes toward statistics (which was assessed by affect, cognitive competence, and value) and that attitudes toward statistics were related to mathematics achievement. Using a longitudinal design, they reported that statistics assessment outcome is correlated more highly with specific attitudes held at the time of the assessment rather than attitudes about statistics which are held by students at the beginning of their statistics course. Furthermore, they found attitudes about cognitive competence are more strongly related to assessment outcomes than previous experience with mathematics, statistics or computing.

Recently, Chiesi and Primi (2010) collected a sample data from 487 undergraduate psychology students enrolled in statistics courses in a university in Italy and investigated the structural relationships among mathematics background, mathematics knowledge, statistics anxiety, attitudes toward statistics and statistics achievement. They reported statistically significant relationship between psychology students' statistics achievement and attitudes toward statistics (assessed by cognitive competence, difficulty, value, and affect). Then, after testing their structural model, they reported statistically significant direct effect of attitudes toward statistics and mathematics knowledge on statistics achievement.

Most recently, it was Emmiouglu in 2011 that studies and develops a model on the subject of structural equation modeling based on the experience in Turkey. She collected data from undergraduate and graduate students (sample size = 247) by adapting the Survey of Attitudes Towards Statistics-36© (SATS-36©) and found positive and statistically significant relationship between students' attitudes toward statistics and both statistics outcomes and mathematics achievement. Furthermore, she reported that most of the participants were doing well at their past as well as overall mathematics courses. She also reported that more than half of the students were willing to use statistics both in the remainder of their degree program and when they are employed. Moreover, she revealed that students generally had positive attitudes toward statistics except that they perceived the difficulty of statistics as neutral and they were indifferent in terms of their individual interest in statistics. Assessing the correlations among constructs, she reported that mathematics achievement was significantly related to statistics outcomes but not to the attitudes toward statistics variables and all of the statistics attitudes variables except difficulty significantly correlated with statistics outcomes. She had used the method of Covariance Based Structural Equation Modeling (CB-SEM) in order to estimate the parameters of her structural model using Mplus 5.21 statistical software. Thus, testing her structural equation model, she reported that affect, cognitive competence, interest and value variables had large total standardized effects on statistics outcomes variable; however, math achievement, and effort had small total effects on explaining statistics outcomes, and difficulty had non-significant total effect on explaining statistics outcomes.

To sum up, a number of structural equation model studies have been conducted with samples varying in majors, nationalities and grade levels. Despite the differences in the samples, instruments and the variables included in these studies, they revealed one common result. That is, students' mathematics skills or mathematics achievement and students' attitudes toward statistics are important factors for explaining students' statistics outcomes.

CHAPTER THREE

DATA AND METHODOLOGY

3.1 Data Sources

The data for this study was obtained from 205 undergraduate Addis Ababa University students who registered for introductory statistics courses offered by the Department of Statistics in the first semester of the 2013/14 Academic Year. For this purpose, a survey design was adopted and a questionnaire was used to gather information from the target population. The target population of the study was all statistics non-major students taking introductory statistics courses offered by the Department of Statistics in the first semester of the 2013/14 academic year in the university. In the current study, the target population was not big enough to conduct a sampling procedure. Therefore, data were aimed to be collected from the whole population.

The frequency and percentages of the participants' majors are presented in Table 3.1. As seen in the table, students were majoring in the areas of Information Science (33.7%), followed by Computer Science (26.8%), Chemistry (25.9%) and Social Anthropology (12.7%).

Table 3.1: Frequency and Percentages of Students' Major (n=205)

Major Field of study	*Frequency*	*Percent*
Information Science	69	33.7
Computer Science	55	26.8
Chemistry	53	25.9
Social Anthropology	26	12.7
Missing	2	1.0

The frequency distribution of participants' class levels were presented in table 3.2. Accordingly, 54.6% of the participants were first year, 40.5% of them were second year, and 3.9% of the participants were third year and above undergraduate students.

Table 3.2: Frequency Distribution of Students' Class Level (n=205)

Students class level	*Frequency*	*Percent*
1st year undergraduate	112	54.6
2nd year undergraduate	83	40.5
3rd year and above undergraduate	8	3.9
Missing	2	1.0

3.2 Data Collection Instruments

The Survey of Attitudes toward Statistics-36© (SATS-36©) was used to collect data (*Appendix A*). The SATS-36© was utilized in this study for many reasons. First, it is a widely used and the most current instrument developed to assess attitudes toward statistics. Second, psychometric properties of the instrument are well documented and supported by confirmatory analysis techniques (Tempelaar et al., 2007). Third, the generation of the subscales was based on a theoretical background (Schau, 2003). Fourth, the instrument is adaptable to different cultures as it has been used across different cultural contexts (Tempelaar et al., 2007; Emmioglu, 2011). The SATS-36© includes 36 items with a seven-point response scale (1 = strongly disagree, 4 = neither disagree nor agree, 7 = strongly agree) in which higher scores correspond to positive attitudes in six subscales: difficulty, value, cognitive competence, affect, effort, and interest. It is especially important to mention that higher scores obtained from the difficulty subscale are interpreted as "students do perceive statistics as an easy subject" (Emmioglu, 2011).

3.3 Variables in the Study

The Outcome (dependent) variable is the variable that is assumed to be predicted by other variable(s) in the model but not assumed to predict any variable presented in the model. For this study, Statistics Outcomes is the dependent variable which is composed of two components: willingness to use statistics in the remainder of the degree program, and willingness to use statistics when employed.

Endogenous latent variables are those variables of the study which are proposed to be predicted by other variables of the hypothesized model. The endogenous latent variables for this study are: Cognitive competence, Interest, Affect, Effort, and Value.

Exogenous latent variables are those variables of the study which are not proposed to be predicted by other variables of the hypothesized model. For this study the exogenous variables are Difficulty and Mathematics Achievement.

3.4 Methodology

3.4.1 Factor Analysis

Firstly, a pilot survey was employed using Post version of the SATS-36© in order to adopt the SATS-36©; and secondly, data were analyzed in order to investigate the score validity and reliability of the survey instrument.

Both exploratory and confirmatory factor analyses were performed to assess the six-factor structure of the Post SATS-36©. SPSS Amos statistical modeling software version 18 was used to run confirmatory factor analysis. IBM SPSS version 20 software was used to run exploratory factor analysis and calculate Cronbach alpha values to examine the internal consistency of the survey subscales.

Prior to the confirmatory factor analysis, exploratory factor analysis was performed with the purpose of sorting out factor structure for the six constructs – affect, cognitive competence, difficulty, effort, interest, and value. The method of Maximum Likelihood was chosen to perform the exploratory factor analysis, and the results revealed the following factor structure and loading values (Table 3.3).

According to the results of exploratory factor analysis, all factors have three indicators each with all indicators having loading values greater than 0.50. For the KMO statistic Kaiser (1974) recommends a bare minimum of .5 and that values between .5 and .7 are mediocre, values between .7 and .8 are good, values between .8 and .9 are great and values above .9 are superb (Hutcheson and Sofroniou, 1991, as cited in Field, 2009).

Table 3.3: Factor loadings, communalities and goodness of fit tests in EFA

FACTORS	Affect	Loading	A6 = 0.740	A4 = 0.703	A3 = 0.692
		Communality	0.608	0.571	0.456
	Competence	Loading	C3 = 0.728	C2 = 0.706	C1 = 0.669
		Communality	0.534	0.672	0.443
	Difficulty	Loading	D6 = 0.824	D7 = 0.761	D5 = 0.750
		Communality	0.742	0.617	0.535
	Effort	Loading	E3 = 0.759	E4 = 0.697	E2 = 0.602
		Communality	0.623	0.455	0.519
	Interest	Loading	I2 = 0.960	I3 = 0.883	I4 = 0.763
		Communality	0.839	0.778	0.656
	Value	Loading	V4 = 0.840	V5 = 0.747	V8 = 0.624
		Communality	0.617	0.658	0.419
Kaiser-Meyer-Olkin Measure of Sampling Adequacy					0.785
Bartlett's Test of Sphericity	Approx. Chi-Square				1532.713
	Df				153
	Sig.				.000
Goodness-of-fit Test	Chi-Square				65.709
	Df				60
	Sig.				.286

In this study, the KMO value is .785, which falls into the range of being good, so we should be confident that the sample size is at least adequate for factor analysis. Bartlett's test of sphericity tests the null hypothesis that the correlation matrix is an identity matrix, which would indicate that the factor model is inappropriate. In this study, since the p-value is small there are significant relationships among the variables. Goodness-of-fit Test is a test of how well a model fits the observed data. Small observed significance levels (say less than 0.10) indicate that the model does not fit well (Field, 2009). In this study the significance level was .286 which indicates that the model fits the data well.

Running the confirmatory factor analysis, all item indicators was allowed to load on its hypothesized factor and all six factors were assumed to be related to each other. Covariation among the item errors was not allowed. The analysis resulted in a χ^2 value of 169.974 with 120 degrees of freedom, and probability level 0.002. In addition to the model chi-square, Comparative Fit Index (CFI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA) fit indices were inspected. Values of these indexes were: CFI = .965, SRMR = .056 and RMSEA = .045 with a confidence interval of .028 to .06.

These values indicated good model fit since CFI values higher than .90, SRMR values smaller than .10, and RMSEA values smaller than .10 are considered favorable (Kline, 2011). After inspecting the overall fit of the model to the data, the standardized parameter estimates are examined (Figure 3.1).

As seen in Figure 3.1 below, the results of the standardized parameters estimates (factor loadings) suggested that the items measured the corresponding factors of the Post SATS-36© well. That is, the standardized estimates of factor loadings ranged from .57 to .90. This finding was consistent with earlier studies (Emmioglu, 2011; Tempelaar et al., 2007).

The results of the latent factor correlations indicated that cognitive competence, value, difficulty, effort and interest are empirically distinguishable constructs (Figure 3.1). The estimated correlation between affect and cognitive competence was highest (r = .59); however, this finding was expected and desired as the same pattern was found in previous studies (Emmioglu, 2011; Tempelaar et al., 2007). Moreover, these constructs are accepted as theoretically and empirically distinct although they are highly correlated (Hilton et al., 2004; Tempelaar et al., 2007). For example, affect and cognitive competence operate empirically different in terms of their relationship with other variables such as with successful completion of a statistics course (Hilton et. al, 2004). In addition, as stated by Tempelaar et al., (2007), the high correlation between affect and cognitive competence is "a remarkable fact" that confirms the theoretical model that the SATS-36© was based on.

For investigating the internal consistency of each subscale, Cronbach alpha coefficients were calculated. The internal consistency reliability estimates were the following: affect =.805, cognitive competence =.767, value =.781, difficulty =.723, interest =.868 and effort =.813.

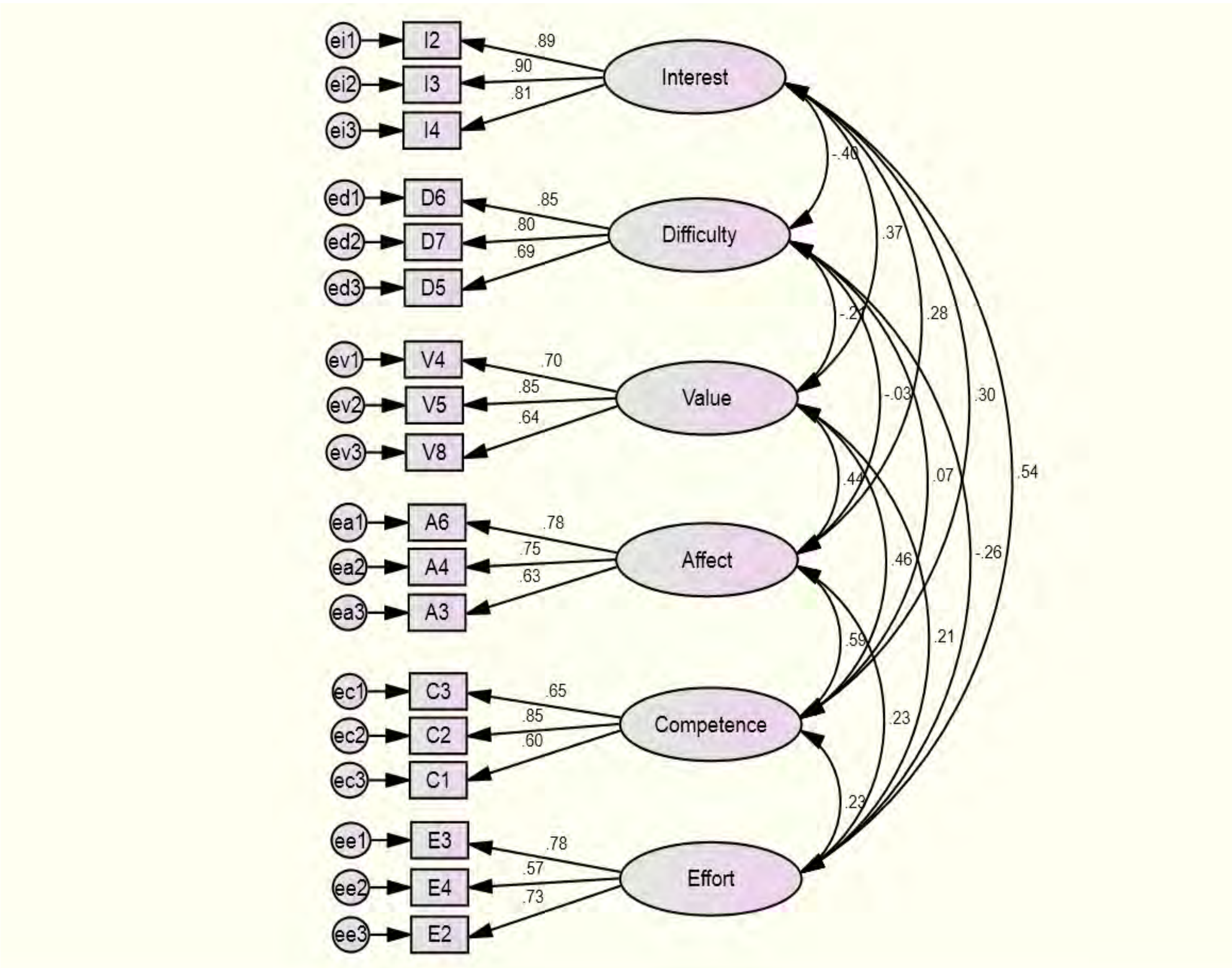

Figure 3.1: Confirmatory Factor Analysis of the Post SATS-36©

Results indicated that difficulty subscale produced adequately reliable scores while the other subscales produced score reliabilities that ranged from "good" to "very good" (Kline, 2011). These values are consistent with previous research, indicating that reliable scores were obtained when the post version of SATS-36© was administered to the sample of the current study as well as to the students from different educational levels, majors, and nationalities (Carnell, 2008; Hilton et al., 2004; Tempelaar et al., 2007; Emmioglu, 2011).

3.4.2 Structural Equation Modeling

Structural Equation Modeling (SEM) was used in order to test the hypothesized model of the study. Structural equation modeling is a general term that has been used to describe a large number of statistical models used to evaluate the validity of substantive theories with empirical data. Statistically, it represents an extension of general linear modeling (GLM) procedures, such as the ANOVA and multiple regression analysis. As a second generation of multivariate analysis technique, SEM offers path analytical modeling with latent variables (Chin, 1998a, as cited in Haenlein and Kaplan, 2004). One of the primary advantages of SEM (vs. other applications of GLM) is that it can be used to study the relationships among latent constructs that are indicated by multiple measures. It is also applicable to both experimental and non-experimental data, as well as cross-sectional and longitudinal data.

SEM takes a confirmatory (hypothesis testing) approach to the multivariate analysis of a structural theory, one that stipulates causal relations among multiple variables. The causal pattern of intervariable relations within the theory is specified a priori. The goal is to determine whether a hypothesized theoretical model is consistent with the data collected to reflect this theory. The consistency is evaluated through *model-data fit*, which indicates the extent to which the postulated network of relations among variables is plausible. SEM is a large sample technique (usually $N >$ 200; Kline, 2011, pp. 111, 178) and the sample size required is somewhat dependent on model complexity, the estimation method used, and the distributional characteristics of observed variables (Kline, 2011, pp. 14–15). In simple terms, SEM involves the evaluation of two models: a structural model and a measurement model (Lei and Wu, 2007).

Structural Model

Structural analysis is an extension of multiple regression in that it involves various multiple regression models or equations that are estimated simultaneously. This provides a more effective and direct way of modeling mediation, indirect effects, and other complex relationship among variables. Path analysis can be considered a special case of SEM in which structural relations among observed (vs. latent) variables are modeled. Structural relations are hypotheses about directional influences or causal relations of multiple variables like how independent variables affect dependent variables (Lei and Wu, 2007).

Measurement Model

The measurement of latent variables is originated from psychometric theories. Unobserved latent variables cannot be measured directly but are indicated or inferred by responses to a number of observable variables (indicators). Latent constructs such as intelligence or reading ability are often gauged by responses to a battery of items that are designed to tap those constructs. Responses of a study participant to those items are supposed to reflect where the participant stands on the latent variable. Statistical techniques, such as factor analysis, exploratory or confirmatory, have been widely used to examine the number of latent constructs underlying the observed responses and to evaluate the adequacy of individual items or variables as indicators for the latent constructs they are supposed to measure (Lei and Wu, 2007).

3.5 SEM Procedures

In general, every SEM analysis goes through the steps of model specification, data collection, model estimation, model evaluation, and (possibly) model modification (Lei and Wu, 2007).

A. Model Specification

A sound model is theory-based. Theory is based on findings in the literature, knowledge in the field, or one's educated guesses, from which causes and effects among variables within the theory are specified. Models are often easily conceptualized and communicated in graphical forms. In these graphical forms, a directional arrow (→) is universally used to indicate a hypothesized causal direction. The variables to which arrows are pointing are commonly termed endogenous variables (or dependent variables) and the variables having no arrows pointing to them are called exogenous variables (or independent variables). Unexplained covariances among variables are indicated by curved arrows (▾▾). Observed variables are commonly enclosed in rectangular boxes and latent constructs are enclosed in circular or elliptical shapes (Lei and Wu, 2007). Below is the hypothesized structural model for this study called "Statistics Attitudes-Outcomes Model" (Emmioglu, 2011).

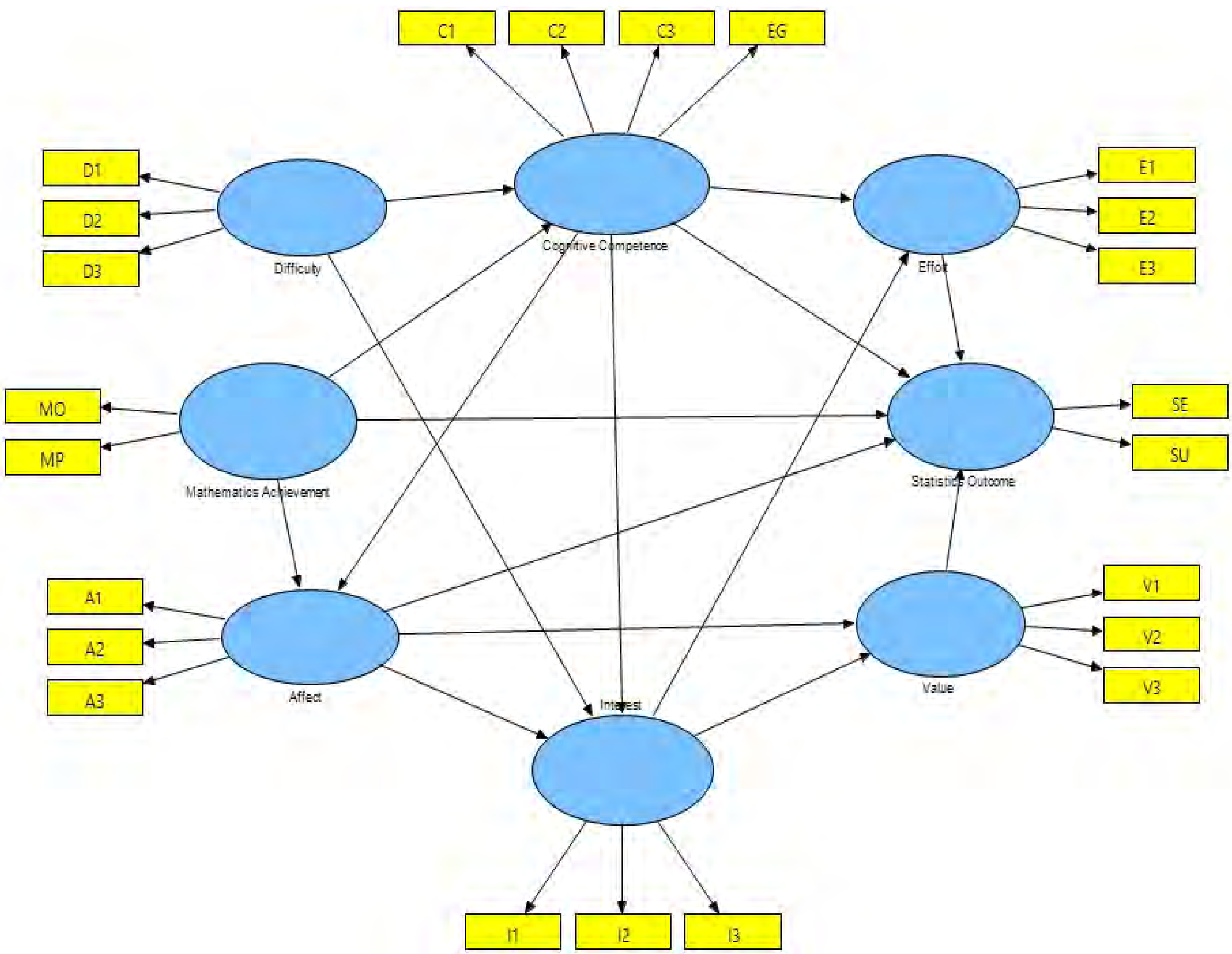

Figure 3.2: The Hypothesized "Statistics Attitudes-Outcomes Model"

Note: The directions of the arrow show the direction of the hypothesized relationships/direct effects among the variables. A1-A3: Affect item indicators, C1-C3: Cognitive Competence item indicators, *V1-V3: Value item indicators, D1-D3: Difficulty item indicators, E1-E3: Effort item indicators; I1-I3: Interest item indicators, MP=Self-reported Previous Math Achievement, MO=Self-reported Overall math achievement, SE= willingness to use statistics when employed, SU= willingness to use statistics in the remainder of the degree program.*

The above hypothesized structural model can also be expressed mathematically (Kaplan, 2001). The structural part of the model can be written as:

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \Gamma\boldsymbol{\xi} + \boldsymbol{\zeta} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where $\boldsymbol{\eta}$ is a vector of endogenous latent variables, $\boldsymbol{\xi}$ is a vector of exogenous (predictor) latent variables, $\mathbf{B}$ is a matrix of regression coefficients relating the latent endogenous variables to each other, Γ is a matrix of regression coefficients relating endogenous variables to exogenous variables, and $\boldsymbol{\zeta}$ is a vector of disturbance terms.

The latent variables are linked to observable variables via measurement equations for the endogenous variables and exogenous variables. These equations are defined as:

$$\mathbf{y} = \boldsymbol{\Lambda}_{\mathrm{y}}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

and,

$$\mathbf{x} = \boldsymbol{\Lambda}_{\mathrm{x}}\boldsymbol{\xi} + \boldsymbol{\delta} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

Where $\boldsymbol{\Lambda}_{\mathrm{y}}$ and $\boldsymbol{\Lambda}_{\mathrm{x}}$ are matrices of factor loadings, respectively, and $\boldsymbol{\varepsilon}$ and $\boldsymbol{\delta}$ are vectors of uniqueness, respectively.

B. Data Characteristics

SEM is a large sample technique. That is, model estimation and statistical inference or hypothesis testing regarding the specified model and individual parameters are appropriate only if sample size is not too small for the estimation method chosen. A general rule of thumb is that the minimum sample size should be no less than 200 (preferably no less than 400 especially when observed variables are not multivariate normally distributed) or 5–20 times the number of parameters to be estimated, whichever is larger (Kline, 2011). Larger models often contain larger number of model parameters and hence demand larger sample sizes (Lei and Wu, 2007).

C. Model Estimation – Partial Least Squares

There are two approaches to estimate the parameters of an SEM, that is, the covariance-based approach (CB-SEM) and the variance-based (PLS-SEM) approach (Haenlein and Kaplan, 2004). For many researchers, SEM is equivalent to carrying out covariance-based SEM (CB□SEM) analyses using software such as Amos, EQS, LISREL, Mplus, and others. But SEM also needs to be thought of as including another unique and very useful approach—partial least squares SEM (Haenlein and Kaplan, 2004).

The covariance-based approach "attempts to minimize the difference between the sample covariances and those predicted by the theoretical model, therefore, the parameter estimation process attempts to reproduce the covariance matrix of the observed measures" (Chin and Newsted, 1999, p. 309), as cited in Haenlein and Kaplan, (2004). CB□SEM develops a theoretical covariance matrix based on a specified set of structural equations. The technique focuses on estimating a set of model parameters in such a way that the difference between the theoretical covariance matrix and the estimated covariance matrix is minimized (Rigdon, 1998), as cited in Hair et al., (2011). The CB□SEM model estimation requires a set of assumptions to be fulfilled, including the multivariate normality of data, minimum sample size, and so forth (Diamantopoulos and Siguaw, 2000), as cited in Hair et al., (2011).

PLS□SEM is, as the name implies, a more "regression-based" approach that minimizes the residual variances of the endogenous constructs. PLS-SEM is a causal modeling approach aimed at maximizing the explained variance of the dependent latent constructs. This is contrary to CB□SEM's objective of reproducing the theoretical covariance matrix, without focusing on explained variance (Hair et al., 2011). In comparison with CB□SEM results, which can be highly imprecise when the assumptions are violated, PLS□SEM often provides a more robust estimate of the structural model (Ringle et al. 2009).

PLS□SEM path modeling can indeed be a "*silver bullet*" for estimating causal models in many theoretical model and empirical data situations (Hair et al. 2011). Its flexibility (i.e., almost no limiting assumptions regarding the model specifications and data) and its comparatively high statistical power make the PLS method particularly adequate for SEM applications that aim at prediction or theory building such as in studies that focus on identifying critical success drivers (Sattler et al., 2010). Finally, PLS□SEM can also be used for confirmatory theory testing (Hair et al., 2011).

Stages and Steps in Calculating the Basic PLS-SEM Algorithm

Let Y_1 denote the dependent latent variable (Statistics Outcome), Y_2 and Y_3 the two exogenous latent variables (Difficulty and Math Achievement), and Y_4, Y_5, Y_6, Y_7 and Y_8 represent the five endogenous latent variables (Interest, Value, Affect, Effort and Cognitive Competence). Further, let X_1 and X_2 denote the two indicator variables used to measure statistics outcome, X_3, X_4, X_5 indicators used to measure difficulty, X_6, X_7 indicators used to measure math achievement, X_8, X_9, X_{10} indicators used to measure interest, X_{11}, X_{12}, X_{13} indicators used to measure value, X_{14}, X_{15}, X_{16} indicators used to measure affect, X_{17}, X_{18}, X_{19} indicators used to measure effort, and lastly, let X_{20}, X_{21}, X_{22} represent the indicators used to measure cognitive competence. Finally, let β_1, $\beta_{2\,...}$ and β_{16} denote the proposed direct effects (regression coefficients) among the study constructs. Hair et. al., (2011) outlines the following stages and steps in calculating the basic PLS-SEM algorithm.

Stage One: Iterative estimation of latent construct scores

Step 1: Outer approximation of latent construct scores (the scores of Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7, and Y_8 are computed based on the manifest variables' scores and the outer coefficients from Step 4)

Step 2: Estimation of proxies for structural model relationships between latent constructs (β_1, $\beta_{2\,...}$ and β_{16})

Step 3: Inner approximation of latent construct scores (based on scores for Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7, and Y_8 from Step 1 and proxies for structural model relationships, β_1, $\beta_{2\,...}$ and β_{16}, from Step 2)

Step 4: Estimation of proxies for coefficients in the measurement models (the relationships between indicator variables and latent constructs or factors loadings with scores from Step 3)

Stage Two: Final estimates of coefficients (outer weights and loadings, structural model

relationships) are determined using the ordinary least squares method for each partial regression in the PLS□SEM model.

D. Model Evaluation

Once model parameters have been estimated, one would like to make a dichotomous decision, either to retain or reject the hypothesized model. This is essentially a statistical hypothesis-testing problem, with the null hypothesis being that the model under consideration fits the data. In order to evaluate the fit of the hypothesized "Statistics Attitudes-Outcomes Model" to the data, several model fit indices were used.

***Model Chi square* (χ^2)** index compares the observed covariance matrix with the expected covariance matrix given the relations among the variables specified by the model. The model chi square is zero when there is no difference between the two matrices (that is, there is perfect fit), and the model chi square index increases as the difference between the matrices increases. A significant model χ^2 value shows that the model predicts relations that are significantly different from the relations observed in the sample, and that the model should be rejected (Dilalla, 2000, as cited in Emmioglu, 2011). There are some problems with relying only on model χ^2 as a fit statistic. It is sensitive to the size of correlations. Larger correlations generally lead to higher values of χ^2. It is also affected by sample size. If the sample size is large, the value of χ^2 may lead to rejection of the model even though differences between observed and predicted covariances are slight (Kline, 2011).

Comparative fit index (CFI) compares the tested model to a null model having no paths that link the variables, therefore making the variables independent of each other. It can range from 0 to 1.0. One group of researchers suggests that scores less than .90 should be considered as unacceptable (Marsh et al., 2004, as cited in Emmioglu, 2011); however, another group suggests that the widely used criteria of .90 should be increased to .95 (Hu and Bentler, 1999, as cited in Emmioglu, 2011).

Root Mean Square Error of Approximation (RMSEA) is a measure of approximate fit in the population and is therefore concerned with the discrepancy due to approximation. A value of zero indicates best fit and higher values indicate a poor fit. RMSEA ≤ 0.05 indicates a close approximate fit, values between 0.08 and 0.10 indicate a mediocre fit, and RMSEA ≥ 0.10 suggests a poor fit (MacCallum et al., 1996).

Standardized Root Mean Square Residual (SRMR) is an overall badness-of-fit measure that is based on the fitted residuals. A value of zero indicates perfect model fit. A rule of thumb is that the SRMR should be less than .05 for a good fit (Hu and Bentler, 1999), whereas values smaller than 0.10 are generally considered favorable (Kline, 2011).

Indicator Reliability: individual item's reliability for reflective constructs is examined by outer loadings. Squaring each of the outer loadings of the individual indicator yields the indicator reliability values. Ken Kwong-Kay Wong, (2013) suggested an indicator reliability value of 0.40 or higher as acceptable.

Internal Consistency Reliability for reflective constructs is measured by composite reliability values. A composite reliability values ≥ 0.60 are generally acceptable (Ken Kwong-Kay Wong, 2013).

Convergent Validity refers to the degree of agreement in two or more measures of the same construct. Evidence of convergent validity is assessed by inspection of variance extracted for each factor (Fornell and Larker, 1981). According to Fornell and Larker, (1981), convergent validity is established, if the variance extracted value exceeds 0.50.

Discriminant Validity is the degree to which any single construct is different from the other constructs in the model. Fornell and Larcker, (1981) suggest that the square root of AVE in each latent variable can be used to establish discriminant validity, if this value is larger than other correlation values among the latent variables.

Coefficient of Determination: the coefficient of determination of the latent endogenous variables is a measure of how well the statistical model is likely to predict outcomes (Hair et al. 2011). In PLS, the coefficient of determination, R-square is the square of the sample correlation coefficient between outcomes and predicted values; and an R^2 values of approximately .67 is substantial, values around .333 are average, and values of .190 and lower are weak (Chin, 1998).

Path Coefficients and Levels of Significance: the path coefficients magnitude indicates the strength and their sign indicates the direction of the relationships among the latent variables. Bootstrapping procedures are used to assess the path coefficients significance (Hair et al., 2011).

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Data Screening

Before analyzing in structural equation modeling, the original data file should be screened for the problems considered next. In this study, first of all, negatively worded items were reversed to make the data ready for the subsequent analyses. Then, data were examined in terms of missing values, normality, linearity, and homoscedasticity (Kline, 2011). Statistical packages SPSS 20, and R 3.02 were used in order to test these assumptions.

4.1.1 Missing Data

In the current study, all the variables except the 'expected-grade' variable (with 4.4% missing values) and 'value5' variable (with 2.4% missing values) had at most 2% missing cases (*Appendix B*). Missing value analysis was conducted to detect whether missing was completely at random (MCAR). Little's Missing Completely at Random |MCAR| test indicated that the missing data pattern was not considered to be completely missing at random since the analysis resulted in a statistically significant chi-square value, χ^2 (437) = 527.982, p = .002. As the data were not missing completely at random, the Expectation-Maximization algorithm was applied to replace the missing values (Pigott, 2001).

4.1.2 Univariate and Multivariate Normality

The results of the tests used for univariate and multivariate normality assumptions analyzed using statistical packages SPSS 20 and R 3.02 respectively were presented in *Appendix C*. Univariate normality of the data distribution was inspected by using both Kolmogorov-Smirnov and Shapiro-

Wilk tests as well as histogram and normal Q-Q plots. The P-values for both tests were zero for all variables indicating that the individual variables are not normally distributed. The inspection of the histogram and normal Q-Q plots also revealed the same result. Mardia's test was used to examine multivariate normality. The test revealed a significant result indicating non-normal multivariate distribution. As a remedy, Partial Least Squares (PLS) parameter estimation method, an estimation method used in SEM analyses which did not require multivariate normality, was used throughout the study (Vinzi et al., 2010).

4.1.3 Linearity and Homoscedasticity

Linearity refers to the linear relationship between variables, when homoscedasticity refers to the assumption that dependent variable(s) exhibit equal levels of variance across the range of predictor variables (Emmioglu, 2011). Linearity and homoscedasticity are the aspects of multivariate normality that can be evaluated by the inspection of bivariate scatter plots (Kline, 2011). In the present study, inspection of bivariate scatter plots resulted in an oval-shaped array of points demonstrating that variables are linearly related and their variances are homogenously distributed.

4.2 Descriptive Statistics

In this part, frequencies and percentages, medians and inter-quartile ranges, and bivariate correlations among the constructs are presented in order to describe participants' characteristics in terms of their mathematics achievement, expectancy of statistics success, willingness to use statistics, and attitudes toward statistics. SPSS 20 statistical software was used to run the descriptive statistics analyses.

4.2.1 Students' Mathematics Achievement

Students were asked to rate their past and overall mathematics achievement from 1 (very poor) to 7 (very well). Of all the students (n=205), 11 (5.4%) students rated their past achievement as 1 out of 7 (very poor); 22 (10.7%) students rated as 2 out of 7; 32 (15.6%) students rated as 3 out of 7, 11 (5.4%) students rated as 4 out of 7 (Have no Knowledge); 44 (21.5%) students rated as 5 out of 7; 59 (28.8%) students rated as 6 out of 7; and 23 (11.2%) students rated as 7 out of 7 (very well). That is, most of the participants (n=126, 61.5%) reported that they were doing well at their past mathematics courses as they rated their past mathematics achievement above the neutral value of four. When students were asked about their overall mathematics achievement, 14 (6.8%) rated their overall mathematics achievement as 1 out of 7 (very poor), 15 (7.3%) rated their overall mathematics achievement as 2 out of 7, 23 (11.2%) students rated as 3 out of 7, 12 (5.9%) students rated as 4 out of 7 (Have no Knowledge), 55 (26.8%) students rated as 5 out of 7, 56 (27.3%) students rated as 6 out of 7, and 26 (12.7%) students rated as 7 out of 7 (very well). These results indicated that most of the participants (n=137, 66.8%) reported their overall mathematics achievement as high since they rated their overall mathematics achievement above the neutral value of four (Table 4.1).

Table 4.1: Frequencies and Percentages for Past and Overall Math Achievement

Ratings	**Past Math Achievement**		**Overall Math Achievement**	
	Frequency	**Percent**	**Frequency**	**Percent**
1	11	5.4	14	6.8
2	22	10.7	15	7.3
3	32	15.6	23	11.2
4	11	5.4	12	5.9
5	44	21.5	55	26.8
6	59	28.8	56	27.3
7	23	11.2	26	12.7
Missing	3	1.5	4	2.0
Total	205	100	205	100

4.2.2 Students' Expectancy of Statistics Success

Frequencies and percentages are presented with regard to students' expectancy of statistics success. Students were asked to write the letter grade that they expect to get after taking their current statistics courses. Of all the students, 8 (3.9%) students stated that they expected to get F, 11 (5.4%) students expected to get Fx, 5 (2.4%) students expected to get D, 5 (2.4%) students expected to get C-, 23 (11.2%) students expected to get C, 20 (9.8%) students expected to get C+, 14 (6.8%) students expected to get B-, 24 (11.7%) students expected to get B, 35 (17.1%) students expected to get B+, 18 (8.8%) students expected to get A-, 22 (10.7%) students expected to get A, and 11 (5.4%) students stated that they expected to get A+ at the end of taking their current introductory statistics courses (Table 4.2). The result indicates that, of all the students 19 (9.3%) students were expecting to fail their statistics courses with F or Fx. Most of the participants (n=144, 70.3%) were expecting to get statistics grades higher than C and more than half of the students (53.7%) were expecting to be successful in their statistics courses by getting statistics grades B or higher.

Table 4.2: Frequencies and Percentages for Expectancy of Success in Statistics Course

Expected grade	**Frequency**	**Percent**
F	8	3.9
Fx	11	5.4
D	5	2.4
C-	5	2.4
C	23	11.2
C+	20	9.8
B-	14	6.8
B	24	11.7
B+	35	17.1
A-	18	8.8
A	22	10.7
A+	11	5.4
Missing	9	4.4
Total	205	100

4.2.3 Students' Willingness to use Statistics

Frequencies and percentages are presented in order to describe students' willingness to use statistics in the remainder of their program of study. Students were asked to rate from 1 (not at all) to 7 (a great deal) to the questions how much they would use statistics when they pursue the remainder of their program of study and how much they would use statistics when they are employed (Table 4.3).

Table 4.3: Frequencies and Percentages for Willingness to Use Statistics (n = 205)

	Willingness to use statistics			
	Remainder of program of study		**When employed**	
Ranking	**Frequency**	**Percent**	**Frequency**	**Percent**
1	16	7.8	13	6.3
2	29	14.1	23	11.2
3	23	11.2	26	12.7
4	51	24.9	48	23.4
5	57	27.8	55	26.8
6	18	8.8	28	13.7
7	9	4.4	10	4.9
Missing	2	1.0	2	1.0
Total	205	100	205	100

From the total of 205 students, 16 (7.8%) rated their use of statistics in the remainder of their program of study as 1 out of 7 (not at all); whereas 29 (14.1%) students rated as 2 out of 7, 23 (11.2%) students rated as 3 out of 7, 51 (24.9%) students rated as 4 out of 7 (neutral), 57 (27.8%) students rated as 5 out of 7, 18 (8.8%) students rated as 6 out of 7, and 9 (4.4%) students rated as 7 out of 7 (a great deal). When students' were asked how much they would use statistics when they are employed, 13 (6.3%) students rated as 1 out of 7 (not at all), 23 (11.2%) students rated as 2 out of 7, 26 (12.7%) students rated as 3 out of 7, 48 (23.4%) rated as 4 out of 7 (neutral), 55 (26.8%) students rated as 5 out of 7, 28 (13.7%) students rated as 6 out of 7, and 10 (4.9%) students rated as 7 out of 7 (a great deal).

As seen in Table 4.3, every two out of five or about 41% of the students were willing to use statistics in the remainder of their degree program, when about a third of the students (n = 68, 33.1%) were not willing to use statistics in the remainder of their degree program, and about a quarter of the students (n = 51, 24.9%) were neutral about using statistics in the remainder of their degree program.

Similarly, about half of the students (n = 93, 45.4%) were willing to use statistics when they are employed when 62 of the students or about 30% were not willing to use statistics when they are employed, and about a quarter of the students (n = 48, 23.4%) were neutral about using statistics when they are employed. In sum, about half of the students were willing to use statistics in the remainder of their degree program and when they are employed.

4.2.4 Students' Attitudes toward Statistics

Median and inter-quartile ranges are presented in order to examine students' attitudes toward statistics (Edmondson, 2005). Median and inter-quartile range values for SATS-36© subscales (affect, cognitive competence, value, difficulty, interest and effort) were measured using a 7-point Likert type scale. Results revealed that students generally had positive attitudes toward statistics. Accordingly, students had positive attitudes toward statistics in terms of effort (M = 5.50, IQR = 2.38), interest (M = 5.00, IQR = 2.50), value (M = 5.00, IQR = 2.50), and cognitive competence (M = 4.75, IQR = 2.50). In terms of affect (M = 4.00, IQR = 2.50) and difficulty subscales (M = 3.00, IQR = 2.00) they had neutral attitudes toward statistics. These results were consistent with previous findings. Data collected on students from the Netherlands (Tempelaar et al, 2007), United States (Carlson & Winquist, 2011; Carnell, 2008), and Turkey (Emmioglu, 2011) revealed similar results that students generally had neutral or positive attitudes toward statistics at the end of taking statistics courses. The median and inter-quartile range values for SATS-36© subscales are presented in Table 4.4.

Table 4.4: Medians and Inter-quartile Ranges for Attitudes toward Statistics (n = 205)

SATS-36© Components	*M*	IQR
Affect	4.00	2.50
Cognitive competence	4.75	2.50
Value	5.00	2.50
Difficulty	3.00	2.00
Interest	5.00	2.50

Effort	5.50	2.38

4.2.5 Correlations among Constructs

Spearman correlations were calculated to make preliminary judgments on complex relationships among study constructs. For this purpose, bivariate correlations between each pair from among cognitive competence, affect, value, difficulty, effort, interest, self-reported mathematics achievement, and statistics outcomes variables were computed. The results of the Spearman correlations are presented in Table 4.5.

Table 4.5: Correlations among Constructs (n = 205)

	1	2	3	4	5	6	7	8
1. Affect	1.00	.55**	.28**	.01	.10	.15*	.16*	.18*
2. Cognitive competence	.55**	1.00	.31**	.07	.16*	.15*	.15*	.20**
3. Value	.28**	.31**	1.00	-.19**	.22**	.19**	.12	.09
4. Difficulty	.01	.07	-.19**	1.00	-.32**	-.19**	-.32**	-.17*
5. Interest	.10	.16*	.22**	-.32**	1.00	.31**	.42**	.36**
6. Effort	.15*	.15*	.19**	-.19**	.31**	1.00	.21**	.27**
7. Statistics outcome	.16*	.15*	.12	-.32**	.42**	.21**	1.00	.37**
8. Math achievement	.18**	.20**	.09	-.17*	.36**	.27**	.37**	1.00

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)

The strength of correlation is often categorized as weak, moderate, or strong. In the current study, the criterion used by Field (2009) was employed. That is, the correlation coefficients of .10 represent low correlation, .30 represent medium correlation and .50 represent strong correlation.

As presented in Table 4.5, the correlation coefficients among statistics outcomes, mathematics achievement and all of the attitudes toward statistics variables except value were statistically significant. The statistically significant correlations were both positive and negative. The correlations between statistics outcomes and cognitive competence ($r = .15$, $p<.05$), affect ($r = .16$, $p<.05$), and effort ($r = .21$, $p<.01$) were weak and statistically significant; correlations between statistics outcomes and difficulty ($r = -.32$, $p<.01$), interest ($r = .42$, $p<.01$), and mathematics achievement ($r = .37$, $p<.01$) were moderate and statistically significant. However, the correlation between statistics outcomes and value was not statistically significant ($r = .12$, $p>.05$), indicating that statistics outcomes are not dependent on students' perceptions about valuing of statistics.

These results showed that students' scores on statistics outcomes were higher when they reported high cognitive competence, effort, affect, and interest scores. That is, the more students had positive affect toward statistics, felt cognitive competence, were interested in statistics, and spent effort to learn statistics the higher their scores on statistics outcomes were.

There was a moderate, statistically significant, and positive correlation between mathematics achievement and statistics outcomes ($r = .37$, $p<.01$); and also, there was statistically significant correlation between math achievement and five of the attitudes toward statistics variables but not with value variable. This result indicated that students who reported high math achievement scores had high statistics outcomes scores; and students' attitudes towards statistics except value were related to their self-reported mathematics achievement.

As seen from the table, there was strong, statistically significant, and positive correlations between affect and cognitive competence ($r = .55$, $p<.01$), indicating that students who reported that they like statistics also reported that they felt cognitive competence.

On the other hand, there were moderate, statistically significant, and positive correlations between affect and value ($r = .28$, $p<.01$), cognitive competence and value ($r = .31$, $p<.01$), interest and effort ($r = .31$, $p<.01$). These results indicated that students who reported that they like statistics also reported that they valued statistics. Students who reported that they felt cognitive competence in statistics also reported that they valued statistics; students who reported that they were interested in statistics reported that they valued statistics.

Then again, there were statistically significant but low correlations between affect and effort ($r = .15$, $p<.05$), cognitive competence and interest ($r = .16$, $p<.05$), cognitive competence and effort ($r = .15$, p<.05), value and interest (r = .22, p<.01), and value and effort (r = .19, p<.01). That is, students who reported that they like statistics also reported that they devoted effort to learn statistics. Students who reported that they felt cognitive competence in statistics also reported that they were interested in statistics, and devoted effort to learn statistics. Students who reported that they were interested in statistics reported that they valued statistics, and students who reported that they valued statistics also reported that they devoted effort to learn and use statistics.

In contrast, there were weak, statistically significant and negative correlations between value and difficulty (r = -.19, p<.01), and effort and difficulty (r = -.19, p<.01), while the correlation between interest and difficulty (r = -.32, p<.01) was moderate, statistically significant and negative. That is, students who reported that they valued statistics, devoted effort on learning and using statistics, and were interested in statistics also reported that they found statistics as an easy subject.

Finally, the correlations between affect and difficulty (r = .01, p>.05), cognitive competence and difficulty (r = .07, p>.05), and affect and interest (r= .10, p>.05) variables were not statistically significant, indicating that students liking of statistics and their individual competence in statistics were independent of their perceptions of the difficulty of statistics as a subject, and students liking of statistics was also independent of their perceptions of interest in statistics.

4.3 Preliminary Analysis

Preliminary analyses were carried out in order to examine whether students in different class levels had different levels of attitudes toward statistics. Medians and ranges were presented to describe students' attitudes toward statistics by their class levels (Table 4.6). Analysis of variance (ANOVA) was conducted for each attitude toward statistics component to investigate whether there was any statistically significant difference in terms of different class levels. In addition to the statistical significance, the effect sizes were calculated.

Table 4.6: Medians and Ranges for Attitudes toward Statistics by Class Levels (n=203)

Components	Class Levels					
	1st Year (n =112)		2nd Year (n = 83)		3rd Year and above (n = 8)	
	M	R	M	R	M	R
Affect	4.42	4.33	3.67	5.83	3.67	2.83
Cognitive Comp.	4.67	5.00	4.17	5.67	4.00	1.00

Difficulty	3.43	3.86	3.57	4.86	3.67	2.57
Value	4.88	3.78	4.25	4.56	4.12	.89
Interest	5.25	6.00	4.50	6.00	4.63	3.75
Effort	5.50	6.00	5.00	6.00	4.63	4.00

ANOVA was conducted for each attitude component to test whether class level had statistically significant impact on the components of attitudes toward statistics.

Prior to the analysis, homogeneity of variances among groups was assessed. Except difficulty and effort components, homogeneity of variances were assumed for all the components as Levene's tests were statistically non-significant, $p>.05$. As multiple significance tests were applied, the alpha level was set to .025 to control for the Type I error, which occurs when a statistical test rejects a true null hypothesis (Field, 2009). For the difficulty and effort components, alpha level was set to .001, as the group variances were significantly different.

The results of the ANOVA revealed that students' interest in statistics, $F(2,200) = 6.81$, $p<.025$, affection to statistics, $F(2,200) = 9.44$, $p<.025$, and value to statistics, $F(2,200) = 5.54$, $p<.025$ were significantly different for the students from different class levels. However, when the strength of the associations was investigated, effect sizes were small for interest, affect, and value components. In other words, class level had small effect on students' interest in statistics, $\eta^2 = .063$, on affection they have to statistics, $\eta^2 = .086$, and on value they give to statistics, $\eta^2 = .053$. In sum, it was assumed that students' coming from different class levels did not distort the results of the current study.

4.4 Model Testing

In order to test the hypothesized structural regression model, the two-step rule was applied. The two-step rule suggests that in order to test a structural regression model firstly, the measurement portion of the model must be identified and, secondly, the structural portion of the model must be identified. In the current study, as a first step, we examined the measures' reliability and validity according to certain criteria associated with reflective measurement model specification (Hair et al., 2011). In the second step, the model with a structural portion was examined.

Partial Least Squares (PLS) parameter estimation method that is robust to non-normality and heterogeneity was used as an estimation method in order to test the measurement and structural portion of the hypothesized structural regression model (Vinzi et al., 2010). Statistical software Smart PLS version 2.0 was used to test both the measurement and structural models.

4.4.1 Measurement Model

The associations among the latent variables (mathematics achievement, difficulty, cognitive competence, affect, interest, value, effort, statistics outcomes) and the indicators (EFA) were tested in an eight factor measurement model by using Smart PLS 2.0 statistical software. Multiple criteria were used to interpret the results of the measurement model tested by a partial least squares parameter estimation method.

4.4.1.1 Outer model loadings and significance

The outer model results suggested that all of the latent variables have strong and highly statistically significant correlations with their corresponding indicators or manifest variables (*Appendix D*). In other words, all factor loadings of the measurement portion were statistically significant, and ranged from .63 (large) to .94 (large). That is, indicator variables were significantly explained by their corresponding latent variables.

4.4.1.2 Indicator Reliability and Validity

It was essential to establish the reliability and validity of the latent variables to complete the examination of the measurement model. The various reliability and validity items that we have checked and reported in this study were summarized in *Appendix E*.

Accordingly, all of the indicators except ‘E4’ and ‘C1’ have individual indicator reliability values that are much larger than the minimum acceptance level of .4 and closer to the preferred level of .7 (Ken Kwong-Kay Wong, 2013). Composite Reliability was used instead of Cronbach’s alpha to measure internal consistency reliability of the latent variables as the latter tend to provide a conservative measurement in PLS-SEM (Hair et al., 2012). As a result, Composite Reliability values were shown to be larger than .6, so high levels of internal consistency reliability have been demonstrated among all eight reflective latent variables. To check convergent validity, each latent variable’s Average Variance Extracted (AVE) was evaluated. It was found that all of the AVE values are greater than the acceptable threshold of 0.5, so convergent validity is confirmed (Ken Kwong-Kay Wong, 2013). Fornell and Larcker (1981) suggest that the square root of AVE in each latent variable can be used to establish discriminant validity, if this value is larger than other correlation values among the latent variables. To do this, a table was created in which the square root of AVE is manually calculated and written in bold on the diagonal in Table 4.7. The correlations between the latent variables are copied from the "Latent Variable Correlation" section of the default report in Smart PLS and were placed in the lower left triangle of the table. As it can be seen from the table, the square roots of AVE for all of the latent variables was found to be larger than the correlation values in their respective columns as well as rows. Thus, the result indicated that discriminant validity was well established.

Table 4.7: Fornell-Larcker Criterion Analysis for Checking Discriminant Validity

	Affect	Cognitive Competence	Difficulty	Effort	Interest	Mathematics Achievement	Statistics Outcome	Value
Affect	**.8234**							
Cognitive Competence	.4699	**.7442**						
Difficulty	-.025	.0260	**.8575**					
Effort	.1825	.2301	-.2059	**.7984**				
Interest	.2384	.3131	-.3411	.4724	**.9118**			
Mathematics Achievement	.2065	.2377	-.0973	.3289	.3553	**.8956**		
Statistics Outcome	.2236	.1856	-.2047	.3032	.4853	.3883	**.9338**	
Value	.3413	.2772	-.1650	.1685	.3143	.0959	.1971	**.8305**

4.4.2 Structural Model

Multiple criteria were used to interpret the estimated Structural Regression model. In addition, parameter estimates were examined to interpret the effects on endogenous variables from other variables presumed to directly predict them. Next, the total effects were examined to interpret the effects on the dependent variable (statistics outcome) from other variables through all presumed ways. In the current study, since we are using a reflective measurement model, the following basic elements were discussed for an initial assessment of PLS-SEM model.

4.4.2.1 Explanation of target endogenous variable variance

The coefficient of determination, R_2=.059 for the Cognitive Competence endogenous latent variable shows that the two exogenous latent variables Difficulty and Mathematics Achievement together explain about 6% of the variation in Cognitive Competence. The coefficient of determination, R^2=.23 for the Affect variable shows that Mathematics Achievement and Cognitive Competence explain 23% of the variation in endogenous latent variable Affect. Similarly, Affect and Interest together explain 17.4% of the variance of Value while Affect, Difficulty and Cognitive Competence together explain about 23% of the variance in Interest, and also Cognitive Competence and Interest together explain about 23% of the variance in Effort. Finally, R^2=.211 for the dependent variable Statistics Outcome which indicates that the exogenous variable Mathematics Achievement and the four endogenous variables; Cognitive Competence, Effort, Affect, and Value together explain about 21% of the variation in the dependent variable Statistics Outcome.

4.4.2.2 Inner model path coefficient sizes and significance

The inner model suggests that Mathematics Achievement has the strongest effect on Statistics Outcome (.303), followed by Effort (.168), Value (.108), Affect (.093) and Cognitive Competence (.001). When running Bootstrapping, results revealed that the hypothesized path relationship between Effort and Statistics Outcome and between Mathematics Achievement and Statistics Outcome were statistically significant at 5% level of significance as their t-statistic exceeds the critical value 1.96. However, the hypothesized path relationship between Value and Statistics Outcome, Affect and Statistics Outcome and Cognitive Competence and Statistics Outcome were not statistically significant as their t-statistic is inferior to the critical value 1.96. Results indicated that the standard errors of the parameters (STERR) ranged from .067 to .088, indicating that the estimates were reasonably determined (*Appendix F*).

The standardized parameter estimates for the structural portion of the model revealed nine out of sixteen statistically significant coefficients, indicating that nine of the sixteen presumed direct effects on endogenous variables from other variables were statistically significant. The statistically significant coefficients ranged from-.346 (small effect) to.446 (medium-effect). The seven non-significant coefficients were the direct effects from Affect to Interest and Statistics Outcome, Cognitive Competence to Effort and Statistics Outcome, Difficulty to Cognitive Competence, Mathematics Achievement to Affect, and finally Value to Statistics Outcome (*Appendix F*). The standardized parameter estimates are presented in Figure 4.1.

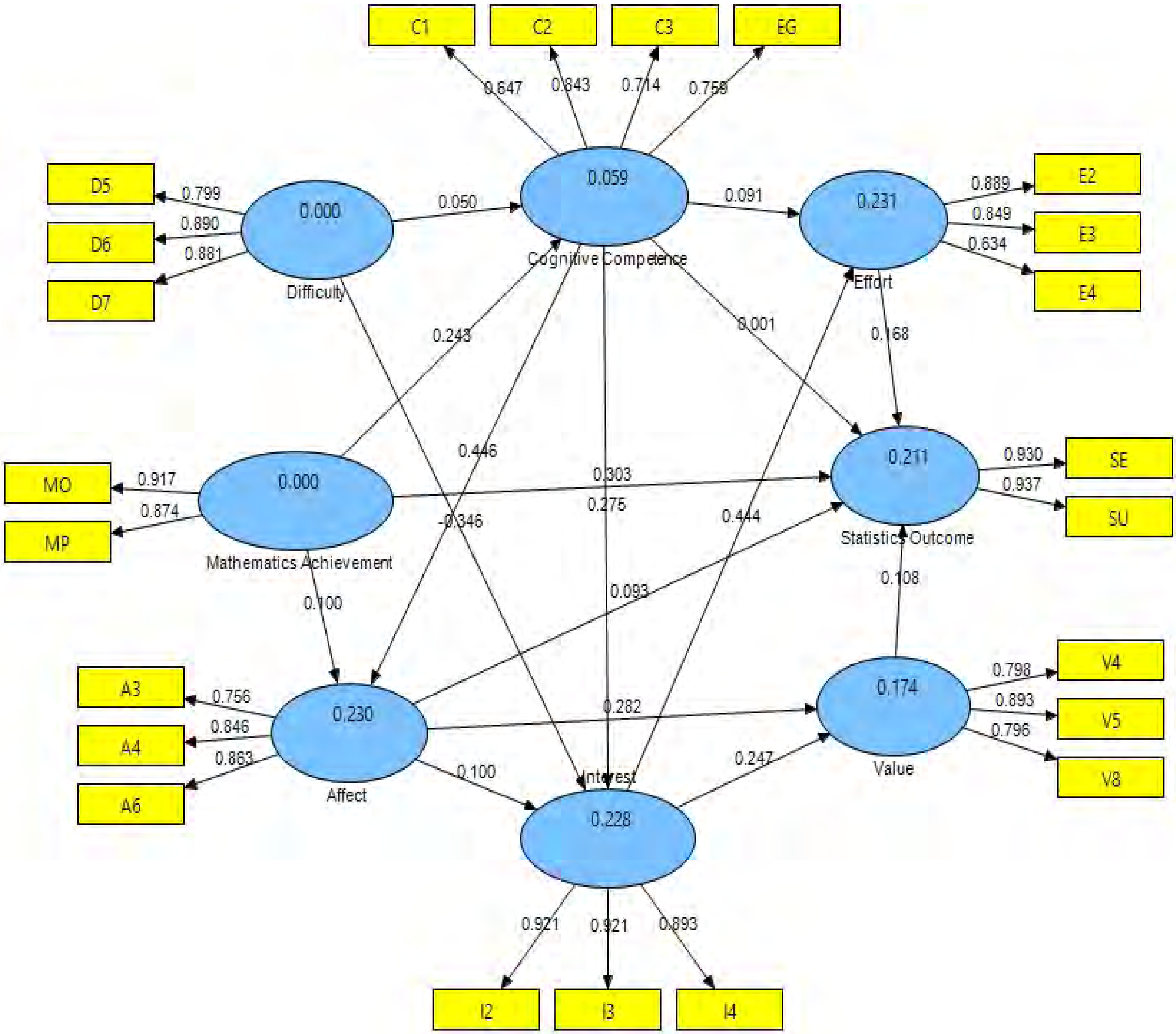

Figure 4.1: The Outer Loadings, R^2 values and Standardized Path Coefficients of the Hypothesized "Statistics Attitudes-Outcome Model"

Note: A3,A4,A6: Affect item indicators, C1,C2,C3: Cognitive Competence item indicators, V4,V5,V8: Value item indicators, D5,D6,D7: Difficulty item indicators, E2,E3,E4: Effort item indicators; I2,I3,I4: Interest item indicators, EG= Expectancy of Success, MP=Previous Math Achievement, MO=Overall math achievement, SE= willingness to use statistics when employed, SU= willingness to use statistics in the remainder of the degree program

Results revealed that mathematics achievement and effort had statistically significant direct effects on statistics outcomes variable while affect had statistically significant direct effect on value. The direct effects of effort (= .168, $t>1.96$) and mathematics achievement (= .303, $t>1.96$) on statistics outcomes were small and medium respectively. That is, when students had higher self-reports of mathematics achievement, and spent more effort in statistics courses they had higher statistics outcomes at the end of their statistics courses.

The direct effect of affect on value was positive and medium (= .282, $t>1.96$), indicating that students who had positive feelings about statistics also valued statistics; and therefore, had higher statistics outcomes at the end of statistics courses. On the other hand, interest had statistically significant direct effects on effort and value variables. The direct effects of interest on effort (= .444, $t>1.96$) and on value (= .247, $t>1.96$) were both positive. In terms of their magnitudes, the direct effect of interest on effort was large while the effect of interest on value was medium. These results indicated that students' interest in statistics predicted their effort for learning statistics and valuing of statistics, which in turn predicted their statistics outcomes at the end of taking statistics courses. In other words, students who had higher interest in statistics valued statistics and spent effort in statistics; and therefore, had higher statistics outcomes at the end of statistics courses.

In turn, cognitive competence and difficulty had statistically significant direct effects on interest variable. The direct effect of difficulty on interest was negative and medium (= -.346, $t>1.96$), indicating that students who perceived statistics as an easy subject were less interested in statistics. The direct effect of cognitive competence on interest was positive and medium (= .275, $t>1.96$). That is, when students had higher cognitive competence in statistics they were more interested in statistics. Cognitive competence had statistically significant direct effect on affect variable. This direct effect was positive and large (= .446, $t>1.96$), indicating that when students had high cognitive competence in statistics they had more positive feelings toward statistics. Lastly, mathematics achievement had statistically significant effect on cognitive competence. This direct effect was positive and medium (= .243, $t>1.96$), indicating that when students had higher self-reports of mathematics achievement their cognitive competence in statistics were high; and therefore, had higher statistics outcomes at the end of statistics courses.

The total standardized effect of a variable is the sum of its total indirect effects and the direct effects. In other words, total effects are the amount of effects via all presumed pathways (Kline, 2011). As statistics outcomes variable is the outcome variable of the study, the total effects on statistics outcomes are the primary interest. The total standardized effects of effort and interest on statistics outcomes were small while that of mathematics achievement on statistics outcomes was medium. More specifically, effort, interest and mathematics achievement had total standardized effects on statistics outcome as .168, .101, and .342 respectively and all of them were statistically significant. However, the total standardized effects of affect, cognitive competence, difficulty, and value variables on statistics outcomes were small and statistically non-significant. These results demonstrated that, effort and interest variables had the smallest contribution to predict statistics outcomes through their all presumed pathways. In addition, mathematics achievement variable had medium contribution to predict statistics outcomes through all its presumed pathways. However, difficulty had no statistically significant contribution to explain statistics outcomes through all its presumed pathways, since the total effects of the difficulty variable were in opposite directions (*Appendix G*).

4.5 Discussion of the results

The main objective of the current study was to investigate the structural relationships among self-reported mathematics achievement, attitudes toward statistics, and statistics outcomes by testing a hypothesized structural equation model, called "Statistics Attitudes-Outcomes Model".

For the overall model fit, the results of the study showed that the hypothesized structural regression model, "Statistics Attitudes-Outcomes Model", was supported with the data. Overall, the hypothesized structural regression model explained about 21% of the variance in statistics outcome variable. Mathematics achievement variable had medium and statistically significant direct effect on statistics outcomes while interest and effort latent variables had small and statistically significant total effects on statistics outcomes. Difficulty, affect, cognitive competence, and value were the variables that had no statistically significant total effects on statistics outcomes variable via all their presumed pathways.

These results indicated that, students' statistics outcomes, which were assessed by their willingness to use statistics after taking statistics courses, were strongly predicted by students' past and overall mathematics achievement. That is, when students had high perceptions of their past and overall mathematics achievement, they had higher statistics outcomes; this means that they were willing to use statistics in the future. In addition, students' interest in statistics and the effort they expand to learn statistics were found as important factors for explaining their statistics outcomes. That is, when they were interested in statistics and spent effort to learn statistics; they became more willing to use statistics in the future.

Results of the current study revealed that effort had small but statistically significant direct effect on statistics outcomes variable. The direction of the effect was positive, indicating that the more students spent effort to learn statistics the higher their statistics outcomes were. This result supported the "Statistics Attitudes-Outcomes Model", and was consistent with Tempelaar et al. (2007) as they reported statistically significant direct effect of effort on students' statistics achievement in a sample of economics and business students (n=1,458) in the Netherlands. Lalonde and Gardner (1993) also reported a statistically significant impact of effort on students' statistics achievement by collecting data from 91 (19 males and 72 females) psychology students in Canada. Emmioglu, (2011) as well revealed that effort had small total effects on explaining statistics outcomes in her study using data collected from 247 undergraduate and graduate students in a university in Turkey.

Similarly, self-reported mathematics achievement variable had statistically significant effect on statistics outcome variable. This result supported the "Statistics Attitudes-Outcomes Model", indicating that when students perceived their current and overall mathematics achievement high, their statistics outcomes were high. This finding is similar to the finding of a study in Israel which showed that a statistically significant direct effect from mathematics aptitude to statistics achievement (Nasser, 2004). A similar study in Turkey also revealed that math achievement had small total effects on explaining statistics outcomes (Emmioglu, 2011). Moreover, a study in Italy using data from 487 undergraduate psychology students revealed statistically significant direct effect of mathematics knowledge on statistics achievement (Chiesi and Primi, 2010). Lalonde and Gardner (1993) also reported statistically significant impact of mathematical aptitude on students' statistics achievement.

Besides cognitive competence had statistically significant and medium direct effect on interest, it had a high, positive, and statistically significant direct effect on affect. This finding also supported the "Statistics Attitudes-Outcomes Model". That is, the higher the participants' cognitive competence in statistics, the higher their positive affect toward statistics. Despite the fact that cognitive competence had a statistically significant direct effect on affect and on interest, no significant direct effect of cognitive competence on effort and statistics outcomes were found, which is contrary to "Statistics Attitudes-Outcomes Model". Tempelaar et al. (2007), found a statistically significant direct effect of cognitive competence on statistics exams and quizzes in a sample of economics and business students ($n = 1,458$) in the Netherlands.

The results of the current study showed that interest had large and statistically significant direct effect on effort while it had medium and statistically significant direct effect on value. This finding supported the "Statistics Attitudes-Outcomes Model". The direction of the direct effect was positive, indicating that the more students were interested in statistics, the more effort they put to learn statistics and the more they valued statistics. The direct effect of cognitive competence on interest was medium and statistically significant and consistent with "Statistics Attitudes-Outcomes Model". This result showed that when participants of the study had higher cognitive competence they were interested in statistics. That is, when students had high cognitive competence in statistics that directly induced them to get interested in statistics. These findings were also partly supported by a study in Turkey (Emmioglu, 2011).

Our results revealed that, value variable had no statistically significant direct effect on statistics outcomes, which contradicted the "Statistics Attitudes-Outcomes Model". Further, this finding was also not in line with Tempelaar et al.'s (2007) study as they reported statistically significant direct effect of value on statistical reasoning in the Netherlands. Comparing these two studies, we can say that students of the current study might have highly succeeded in statistics even though they did not appreciate the value of statistics.

In the current study, it was interesting to find that, the direct effects of affect on statistics outcomes were not statistically significant but it has medium and statistically significant direct and total effects on value. Therefore, the current study demonstrated that students' affect toward statistics is an important factor for explaining the value students attributed to statistics. This relationship was also positive. That is, the more students positive affect toward statistics the more they valued statistics. Contrary to this finding Emmioglu (2011) reported that affect had large total standardized effect on statistics outcomes variable.

Another interesting finding was that the direct and total effects of difficulty on interest were in opposite directions. Difficulty had a medium and statistically significant direct effect on interest. This finding was consistent with the "Statistics Attitudes-Outcomes Model". That is, students' perception of the difficulty of statistics was a statistically significant predictor of interest. However, as stated earlier, the interesting point is that the direct effect from difficulty on interest was negative. These results agree with Emmiouglu, (2011) who reported a negative relationship between interest and difficulty in a study of graduate students from education disciplines (n = 247) in Turkey. That is to say, students' were less interested in statistics when they thought that statistics was an easy subject. Therefore, the total effect of difficulty on interest was invisible (Emmiouglu, 2011).

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Descriptive analyses indicated that participants of the study had self-reports of high past and overall mathematics achievement. Participants were willing to use statistics in the future and they are hopeful to pass their current statistics courses. They generally reported positive attitudes toward statistics except that they perceived the difficulty of statistics as neutral and they were indifferent in terms of their individual affection to statistics. Descriptive results also demonstrated that students' scores from different attitudes toward statistics variables were generally correlated with each other. Mathematics achievement was significantly related to statistics outcomes and to all of the attitudes toward statistics variables but not to value. All of the statistics attitudes variables except value significantly correlated with statistics outcomes.

Structural equation modeling analyses indicated that overall, the hypothesized structural regression model explained about 21% of the variance in statistics outcome variable. All of the indicators in the model were explained by their corresponding factors significantly. The measurement and structural regression models fitted the data well. Mathematics achievement variable had medium total standardized effects on statistics outcomes variable; however, effort and interest variables had small total effects on explaining statistics outcomes, and difficulty had non-significant total effect on explaining statistics outcomes.

5.2 Recommendations

Based on the study findings and keeping the limitations in mind, the study puts forward the following recommendations:

- Future researchers should try to include direct measures, such as students' statistics grades at the end of taking statistics courses to measure statistics outcome variable, for assessing students' statistics achievement.

- ❖ 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.
- ❖ It is suggested for future research to examine the direct effect from interest to statistics outcome which in turn may increase the coefficient of determination of the dependent variable statistics outcome.
- ❖ Students' attitudes should be given high priority when designing and implementing statistics curricula.
- ❖ Statistics instructors should employ statistics activities that are interesting for students to participate which would help students to have more interest toward statistics.
- ❖ Finally, it is suggested for instructors to use appropriate instructional methods that use technology to increase students' positive attitudes toward statistics.

REFERENCES

Ajzen, I. (2005). *Attitudes, personality, and behavior (2nd ed.). New York: Open University Press.*

Ben-Zvi, D. and Garfield, J. (2010). *Introducing the emerging discipline of statistics education. School Science and Mathematics, 108(8), 355-361.*

Bluman A.G, (2012). *Elementary Statistics: a step by step approach, 8th Edition. The McGraw-Hill Companies, Inc. All rights reserved © 2012.*

Carlson, K. A. and Winquist, J. R. (2011). *Evaluating an active learning approach to teaching introductory statistics: A classroom workbook approach. Journal of Statistics Education, 19.*

Carnell, L. J. (2008). *The effect of a student-designed data collection project on attitudes toward statistics. Journal of Statistics Education, 16. Retrieved January 28, 2014, from* www.amstat.org/publications/jse/v16n1/carnell.html.

Chiesi, F. and Primi, C. (2010). *Cognitive and non-cognitive factors related to students' statistics achievement. Statistics Education Research Journal, 9(1), 6-26.*

Chin W.W,(1998). *Issues and Opinion on Structural Equation Modeling; Management Information Systems Quarterly; Volume 22, Number 1.*

delMas, R. C., Garfield, J. and Chance, B. L. (1999). *A model of classroom research in action: Developing simulation activities to improve students' statistical reasoning. Journal of Statistics Education, 7, Retrieved December 3, 2014, from* http://www.amstat.org/publications/jse/secure/v7n3/delmas.cfm.

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

Edmondson D. R. (2005). Likert Scales: A History. CHARM database, 2005.

Emmioglu, E. (2011). *A Structural Equation Model Examining the Relationships Among Mathematics Achievement, Attitudes Toward Statistics, And Statistics Outcomes. Middle East Technical University. Published PhD Dissertation.*

Evans, B. (2007). *Student attitudes, conceptions, and achievement in introductory undergraduate college statistics. The Mathematics Educator, 17(2), 6.*

Field, A. P. (2009). *Discovering Statistics Using SPSS (3rd ed.). Sage Publications.*

Fornell, C. and Larcker, D.F., (1981). *Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18 (1), 39-50.*

Gal, I. and Ginsburg, L. (1994). *The role of beliefs and attitudes in learning statistics: Towards an assessment framework. Journal of Statistics Education 2. Retrieved December 10, 2014, from* http://www.amstat.org/publications/jse/v2n2/gal.html

Garfield, J., Hogg, B., Schau, C. and Whittinghill, D. (2002). *First courses in statistical science: The status of educational reform efforts. Journal of Statistics Education, 10. Retrieved December 12, 2014, from* www.amstat.org/publications/jse/v10n2/garfield.html.

Haenlein, M. and Kaplan A.M. (2004). *A Beginner's Guide to Partial Least Squares Analysis, UNDERSTANDING STATISTICS, 3(4), 283–29. Copyright © 2004, Lawrence Erlbaum Associates, Inc.*

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011): *PLS-SEM: Indeed a Silver Bullet. Journal of Marketing Theory and Practice, vol. 19, no. 2 (spring 2011), pp. 139–151. © 2011 M.E. Sharpe, Inc. All rights reserved.*

Hand, D. J. (1998). *Breaking misconceptions - statistics and its relationship to mathematics. The Statistician, 47(2), 245-250.*

Hilton, S. C., Schau, C. and Olsen, J. A. (2004). *Survey of attitudes toward statistics: Factor structure invariance by gender and by administration time. Structural Equation Modeling, 11(1), 92-109.*

Johnson, M. and Kuennen, E. (2006). *Basic math skills and performance in an introductory statistics course. Journal of Statistics Education, 14. Retrieved November 17, 2014, from* www.amstat.org/publications/jse/v14n2/johnson.html.

Kaplan D. (2001). *Structural Equation Modeling: Foundations and Extensions. International Encyclopedia of the Social & Behavioral Sciences, Elsevier Science Ltd.*

Ken Kwong-Kay Wong, (2013): *Partial Least Squares Structural Equation Modeling (PLS-SEM) Techniques Using SmartPLS, Marketing Bulletin, 2013, 24, Technical Note 1*

Kline, R. B. (2011). *Principles and practice of structural equation modeling (3rd ed.). New York: Guilford.*

Lalonde, R. N. and Gardner, R. C. (1993). *Statistics as a second language? A model for predicting performance for psychology students. Canadian Journal of Behavioural Science 25(1), 108-125.*

learned helplessness. (2014). *Encyclopædia Britannica Online*. Retrieved 13 February, 2014, from http://www.britannica.com/EBchecked/topic/1380861/learned-helplessness

Lei Pui-Wa and Qiong Wu, (2007): *An NCME Instructional Module on Introduction to Structural Equation Modeling, pp.34-36.*

MacCallum, R. C., Browne, M. W., and Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*(2), 130-149.

Nasser, F. M. (2004). *Structural model of the effects of cognitive and affective factors on the achievement of Arabic-speaking pre-service teachers in introductory statistics. Journal of Statistics Education, 12. Retrieved November 17, 2014, from www.amstat.org/publications/jse/v12n1/asser.html.*

Onwuegbuzie, A. J. (2003). *Modeling statistics achievement among graduate students. Educational and Psychological Measurement, 63(6), 1020-1038.*

Perney, J., and Ravid, R. (1991), *"The Relationship Between Attitudes Towards Statistics, Math Self-Concept, Test Anxiety and Graduate Students' Achievement in an Introductory Statistics Course," National College of Education, Evanston, IL.*

Peterson, I. (1991), *"Pick a Sample," Science News, 140, 56-58.*

Pigott, T.D. (2001). *A Review of Methods for Missing Data; Educational Research and Evaluation; 2001, Vol. 7, No. 4, pp. 353-383 © Swets & Zeitlinger.*

Ringle, C.M., Götz, O., Wetzels, M. and Wilson B. (2009), *"On the Use of Formative Measurement Specifications in Structural Equation Modeling: A Monte Carlo Simulation Study to Compare Covariance-Based and Partial Least Squares Model Estimation Methodologies," METEOR Research Memoranda RM/09/014, Maastricht University.*

Sattler, H. Völckner, F., Riediger, C. and Ringle, C.M. (2010), *"The Impact of Brand Extension Success Factors on Brand Extension Price Premium," International Journal of Research in Marketing, 27 (4), 319–328.*

Schau, C. (2003). *Students' attitudes: The "Other" important outcome in statistics education. Paper presented at the Joint Statistical Meeting, Section on Statistics Education,* *San Francisco, CA.*

Schau, C. (2005). *View SATS. Retrieved Novemeber 25, 2014 from* *http://www.evaluationandstatistics.com/view.html©.*

Suanpang, P., Petocz, P. and Kalceff, W. (2004). *Student attitudes to learning business statistics: Comparison of online and traditional methods. Journal of Educational Technology & Society, 7(3), 9-20.*

Tempelaar, D. T., Schim van der Loeff, S. and Gijselaers, W. H. (2007). *A structural equation model analyzing the relationship of students' attitudes toward statistics, prior reasoning abilities and course performance. Statistics Education Research Journal, 6(2), 78-102.*

Vinzi, V.E, Trinchera L, and Silvano A. (2010). *PLS Path Modelling: From Foundations to Recent Developments and Open Issues for Model Assessment and Improvement. Handbook of Partial Least Squares, Springer Handbooks.*

Wiberg, M. (2009). *Teaching statistics in integration with psychology. Journal of Statistics Education, 17.*

APPENDICES

APPENDIX A: *Questionnaire*

Survey of Attitudes Toward Statistics (Post)

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The statements below are designed to identify your attitudes about statistics. The responses range from **1 (strongly disagree), 2(disagree), 3(slightly disagree), 4(neither disagree nor agree), 5(slightly agree), 6(agree), 7(strongly agree)**.

S.No	Item	Responses						
	Affect							
1	I like statistics	1	2	3	4	5	6	7
2	I feel insecure when I have to do statistics problems	1	2	3	4	5	6	7
3	I get frustrated going over statistics tests in class	1	2	3	4	5	6	7
4	I am under stress during statistics courses	1	2	3	4	5	6	7
5	I enjoy taking statistics courses	1	2	3	4	5	6	7
6	I am scared by statistics	1	2	3	4	5	6	7
	Cognitive Competence							
7	I have trouble understanding statistics because of how I think	1	2	3	4	5	6	7
8	I have no idea of what's going on in this statistics course	1	2	3	4	5	6	7
9	I make a lot of math errors in statistics	1	2	3	4	5	6	7
10	I can learn statistics	1	2	3	4	5	6	7
11	I understand statistics equations	1	2	3	4	5	6	7
12	I find it difficult to understand statistical concepts	1	2	3	4	5	6	7
	Value							
13	Statistics is worthless	1	2	3	4	5	6	7
14	Statistics should be a required part of my professional training	1	2	3	4	5	6	7
15	Statistical skills will make me more employable	1	2	3	4	5	6	7
16	Statistics is not useful to the typical professional	1	2	3	4	5	6	7
17	Statistical thinking is not applicable in my life outside my job	1	2	3	4	5	6	7
18	I use statistics in my everyday life	1	2	3	4	5	6	7
19	Statistics conclusions are rarely presented in everyday life	1	2	3	4	5	6	7
20	I will have no application for statistics in my profession	1	2	3	4	5	6	7
21	Statistics is irrelevant in my life	1	2	3	4	5	6	7
	Difficulty							
22	Statistics formulas are easy to understand	1	2	3	4	5	6	7
23	Statistics is a complicated subject	1	2	3	4	5	6	7
24	Statistics is a subject quickly learned by most people	1	2	3	4	5	6	7

25	Learning statistics requires a great deal of discipline	1	2	3	4	5	6	7
26	Statistics involves massive computations	1	2	3	4	5	6	7
27	Statistics is highly technical	1	2	3	4	5	6	7
28	Most people have to learn a new way of thinking to do statistics	1	2	3	4	5	6	7
	Interest							
29	I am interested in being able to communicate statistical information to others	1	2	3	4	5	6	7
30	I am interested in using statistics	1	2	3	4	5	6	7
31	I am interested in understanding statistical information	1	2	3	4	5	6	7
32	I am interested in learning statistics	1	2	3	4	5	6	7
	Effort							
33	I tried to complete all of my statistics assignments	1	2	3	4	5	6	7
34	I worked hard in my statistics course	1	2	3	4	5	6	7
35	I tried to study hard for every statistics test	1	2	3	4	5	6	7
36	I tried to attend every statistics class session	1	2	3	4	5	6	7
NOTICE that the labels for the scale on each of the following items differ from those used above. Here, 1(very poorly), 2(poorly), 3(slightly poorly), 4(have no knowledge), 5(slightly well), 6(well), 7(very well)								
1	How well did you do in mathematics courses you have taken in the past?	1	2	3	4	5	6	7
2	How good at mathematics are you?	1	2	3	4	5	6	7
NOTICE that the labels for the scale on each of the following items differ from those used above. Here, 1(not at all), 2(very little), 3(little), 4(somewhat), 5(much), 6(very much), 7(a great deal)								
1	As you complete the remainder of your degree program, how much will you expect to use statistics?	1	2	3	4	5	6	7
2	In the field in which you hope to be employed when you finish school, how much will you expect to use statistics?	1	2	3	4	5	6	7
DIRECTIONS: For each of the following statements circle the one best response. Notice that the response scale changes on each item.								
1	In which class are you studying currently? 1. 1st year 2. 2nd year 3. 3rd year 4. 4th year and above							
2	What is your major? 1. Chemistry 2. Computer Science 3. Sociology 4. Information Science							
3	How confident are you that you have mastered introductory statistics material? 1. Not at all confident 2.Very little confident 3.Little confident 4. Somewhat confident 5.Much confident 6.Very much confident 7. Great confidence							
4	How difficult for you is the material currently being covered in this course?							

EG	196	7.44	2.965	9	4.4	0	0

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

EM Estimated Statistics

EM Means[a]

A3	A4	A6	C1	C2	C3	V4	V5	V8	D5	D6	D7	I2	I3	I4	E2	E3	E4	MP	MO	SU	SE	EG
4.00	4.26	4.11	4.38	4.79	3.87	5.06	5.05	4.70	3.43	3.09	3.40	4.50	4.68	4.51	4.77	4.86	5.24	4.60	4.75	3.95	4.15	7.44

a. Little's MCAR test: Chi-Square = 527.982, DF = 437, Sig. = .002

APPENDIX C: Univariate and Multivariate Normality

Selected Output:

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
A3	.170	205	.000	.923	205	.000
A4	.191	205	.000	.887	205	.000
A6	.157	205	.000	.905	205	.000
C1	.148	205	.000	.915	205	.000
C2	.233	205	.000	.870	205	.000
C3	.145	205	.000	.929	205	.000
V4	.218	205	.000	.880	205	.000
V5	.209	205	.000	.866	205	.000
V8	.187	205	.000	.901	205	.000
D5	.155	205	.000	.919	205	.000
D6	.214	205	.000	.875	205	.000
D7	.178	205	.000	.891	205	.000
I2	.237	205	.000	.872	205	.000
I3	.233	205	.000	.872	205	.000
I4	.229	205	.000	.850	205	.000
E2	.213	205	.000	.888	205	.000
E3	.205	205	.000	.891	205	.000
E4	.252	205	.000	.814	205	.000
MP	.213	205	.000	.899	205	.000
MO	.240	205	.000	.887	205	.000
SU	.176	205	.000	.936	205	.000
SE	.164	205	.000	.942	205	.000
EG	.137	205	.000	.947	205	.000

a. Lilliefors Significance Correction

> mardia(Data_Frame, na.rm = TRUE, plot=TRUE)

Call: mardia(x = Data_Frame, na.rm = TRUE, plot = TRUE)

Mardia tests of multivariate skew and kurtosis

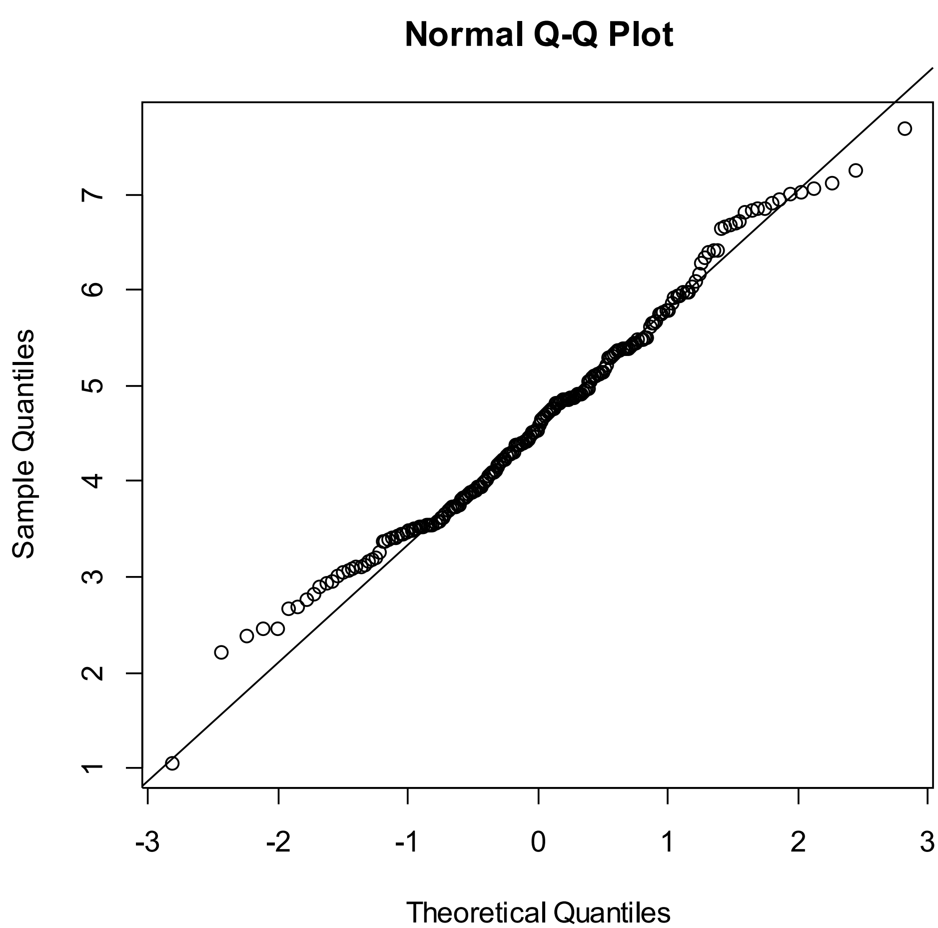
Use describe(x) the to get univariate tests

n.obs = 205   num.vars = 23

b1p = 107.67   skew = 3678.64 with probability = 0

small sample skew = 3737.01 with probability = 0

b2p = 652.29   kurtosis = 16.32 with probability = 0



APPENDIX D: ***Results Summary for Reflective Outer Model***

Latent Variables	Indicators	Loadings	Original Samples (O)	Standard Error (STERR)	t-statistic (|O/STERR|)
Affect	A3	.7564	.7564	.0532	14.2246*
	A4	.8464	.8464	.0264	32.0685*
	A6	.8633	.8633	.0228	37.8907*
Cognitive Competence	C1	.6470	.6470	.0919	7.0380*
	C2	.8431	.8431	.0342	24.6624*
	C3	.7142	.7142	.0689	10.3718*
	EG	.7591	.7591	.0625	12.1461*
Difficulty	D5	.7988	.7988	.0627	12.7346*
	D6	.8897	.8897	.0275	32.3185*
	D7	.8812	.8812	.0270	32.5963*
Effort	E2	.8885	.8885	.0223	39.8739*
	E3	.8491	.8491	.0322	26.3487*
	E4	.6341	.6341	.0950	6.6715*
Value	V4	.7980	.7980	.0521	15.3051*
	V5	.8933	.8933	.0213	41.9662*
	V8	.7964	.7964	.0467	17.0702*
Interest	I2	.9211	.9211	.0133	69.0080*
	I3	.9214	.9214	.0182	50.7091*
	I4	.8927	.8927	.0220	40.4840*
Statistics Outcome	SE	.9301	.9301	.0150	61.9494*
	SU	.9374	.9374	.0110	85.5017*
Mathematics Achievement	MO	.9166	.9166	.0195	46.9955*
	MP	.8741	.8741	.0347	25.1799*

*t>1.96

APPENDIX E: ***Indicator Reliability and Validity***

Latent Variables	Indicators	Loadings (l)	Indicator Reliability (l^2)	Composite Reliability	AVE
Affect	A3	.7564	.5721	.8629	.6780
	A4	.8464	.7164		
	A6	.8633	.7453		
Cognitive Competence	C1	.6470	.4186	.8311	.5539
	C2	.8431	.7108		
	C3	.7142	.5101		
	EG	.7591	.5762		
Difficulty	D5	.7988	.6381	.8927	.7354
	D6	.8897	.7916		
	D7	.8812	.7765		
Effort	E2	.8885	.7894	.8380	.6375
	E3	.8491	.7209		
	E4	.6341	.4021		
Value	V4	.7980	.6368	.8693	.6897
	V5	.8933	.7979		
	V8	.7964	.6343		
Interest	I2	.9211	.8484	.9367	.8314
	I3	.9214	.8489		
	I4	.8927	.7969		
Statistics Outcome	SE	.9301	.8651	.9316	.8719
	SU	.9374	.8787		
Mathematics Achievement	MO	.9166	.8402	.8901	.8021
	MP	.8741	.7641		

APPENDIX F: ***Mean, Standard error and t-values for Path Coefficients***

Path	Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	t-statistic (|O/STERR|)
Affect - > Interest	.1004	.1002	.0722	1.3911
Affect - > Statistics Outcome	.0930	.0880	.0830	1.1203
Affect - > Value	.2824	.2868	.0709	3.9818*
Cognitive Competence - > Affect	.4460	.4499	.0715	6.2366*
Cognitive Competence -> Effort	.0911	.0939	.0763	1.1941
Cognitive Competence -> Interest	.2750	.2778	.0789	3.4854*
Cognitive Competence -> Statistics Outcome	.0014	.0013	.0793	.0179
Difficulty - > Cognitive Competence	.0496	.0495	.0876	.5663
Difficulty - > Interest	-.3457	-.3491	.0671	5.1535*
Effort - > Statistics Outcome	.1680	.1734	.0834	2.0158*
Interest - > Effort	.4439	.4481	.0750	5.9151*
Interest - > Value	.2470	.2478	.0766	3.2265*
Mathematics Achievement - > Affect	.1005	.1016	.0699	1.4373
Mathematics Achievement - > Cognitive Competence	.2425	.2465	.0789	3.0744*
Mathematics Achievement - > Statistics Outcome	.3032	.3037	.0683	4.4396*
Value - > Statistics Outcome	.1076	.1098	.0833	1.2920

*t>1.96

APPENDIX G: ***Total Effects (Mean, STERR, t-value)***

Paths	Original Sample (O)	Sample Mean (M)	Standard Error (STERR)	t-statistics (|O/STERR|)
Affect - > Effort	.0446	.0440	.0324	1.3772
Affect - > Interest	.1004	.1003	.0715	1.4033
Affect - > Statistics Outcome	.1335	.1321	.0794	1.6807
Affect - > Value	.3072	.3115	.0703	4.3724*
Cognitive competence - > Affect	.4460	.4510	.0703	6.3456*
Cognitive competence - > Effort	.2330	.2373	.0763	3.0532*
Cognitive competence - > Interest	.3197	.3233	.0709	4.5080*
Cognitive competence - > Statistics Outcome	.1041	.1090	.0765	1.3606
Cognitive competence - > Value	.2049	.2109	.0452	4.5370*
Difficulty - > Affect	.0221	.0197	.0392	.5649
Difficulty - > Cognitive competence	.0496	.0451	.0860	.5769
Difficulty - > Effort	-.1419	-.1458	.0449	3.1608*
Difficulty - > Interest	-.3299	-.3344	.0725	4.5513*
Difficulty - > Statistics Outcome	-.0298	-.0345	.0197	1.5156
Difficulty - > Value	-.0752	-.0782	.0358	2.1016*
Effort - > Statistics Outcome	.1680	.1724	.0835	2.0120*
Interest - > Effort	.4439	.4451	.0743	5.9766*
Interest - > Statistics Outcome	.1012	.1082	.0426	2.3734*
Interest - > Value	.2470	.2496	.0754	3.2755*
Mathematics Achievement - > Affect	.2086	.2116	.0760	2.7442*
Mathematics Achievement - > Cognitive competence	.2425	.2466	.0777	3.1229*
Mathematics Achievement - > Effort	.0610	.0662	.0308	1.9815*

Mathematics Achievement - > Interest	.0876	.0939	.0366	2.3966*
Mathematics Achievement - > Statistics Outcome	.3418	.3432	.0637	5.3642*
Mathematics Achievement - > Value	.0806	.0837	.0305	2.6430*
Value - > Statistics Outcome	.1076	.1091	.0840	1.2808

*t>1.96