A STRUCTURAL EQUATION MODEL EXAMINING THE RELATIONSHIPS AMONG MATHEMATICS ACHIEVEMENT, ATTITUDES TOWARD STATISTICS, AND STATISTICS OUTCOMES

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ABSTRACT

A STRUCTURAL EQUATION MODEL EXAMINING THE RELATIONSHIPS AMONG MATHEMATICS ACHIEVEMENT, ATTITUDES TOWARD STATISTICS, AND STATISTICS OUTCOMES

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The purpose of the current study was to investigate the structural relationships among self-reported mathematics achievement, attitudes toward statistics, and statistics outcomes by testing a structural model. The current study utilized a survey design. The participants of study consisted of 247 undergraduate and graduate students enrolled in statistics courses in a university in Turkey. The participants were from different disciplines such as engineering, education, and economics. The Turkish version of the Survey of Attitudes toward Statistics-36© (SATS-36©) was used to collect data. The SATS-36© assessed six components of statistics attitudes: cognitive competence, value, difficulty, effort, interest, and affect. Higher scores of the six components referred to the more positive attitudes. In addition, the SATS-36© involved additional items to measure students' self-reports of mathematics achievement and statistics outcomes. Results of the descriptive statistics analyses revealed that participants of the study had positive attitudes toward statistics except that they had neutral perceptions about the difficulty of statistics and neutral interest in statistics. Statistics outcomes variable was significantly correlated with mathematics achievement, affect, value, interest, and effort variables. Structural equation modeling was used to test the hypothesized structural regression model. Results indicated that affect, value, cognitive competence, and interest variables had large total standardized effects on statistics outcomes variable. Mathematics achievement and the effort variables had small total effects on explaining statistics outcomes. Difficulty had no statistically significant total effect on explaining statistics outcomes. Overall, the hypothesized structural regression model explained 66% of the total variance in statistics outcomes, which was statistically significant.

Keywords: Attitudes toward Statistics, Self Reported Mathematics Achievement, Statistics Outcomes, Structural Equation Model

ÖZ

MATEMATİK BAŞARISI, İSTATİSTİĞE YÖNELİK TUTUMLAR VE İSTATİSTİK KAZANIMLARI ARASINDAKİ İLİŞKİLERİ İNCELEYEN YAPISAL EŞİTLİK MODELİ

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Bu çalışmanın amacı matematik başarısı, istatistiğe yönelik tutumlar ve istatistik kazanımları arasındaki yapısal ilişkilerin incelenmesidir. Çalışmada tarama deseni kullanılmıştır. Katılımcılar, Türkiye'de bir üniversitede lisans ve lisansüstü eğitimlerini sürdüren ve istatistik dersi alan 247 öğrenciden oluşmaktadır. Katılımcılar mühendislik, iktisat, eğitim gibi farklı alanlarda öğrenim görmektedir. Veriler Tükçe'ye uyarlanan İstatistiğe yönelik Tutum Anketi (İYTA) kullanılarak toplanmıştır. İstatistiğe yönelik Tutum Anketi, istatistik tutumlarının altı alt boyutunu ölçmektedir. Bunlar bilişsel yeterlilik, değer, zorluk, çaba, ilgi ve duygudur. Bu boyutlardan alınan yüksek puanlar öğrencilerin istatistiğe yönelik olumlu tutumlarının olduğunu göstermektedir. İstatistiğe yönelik Tutum Anketi, öğrencilerin matematik başarıları ile ilgili kişisel görüşleri ve istatistik kazanımlarını ölçen ek maddeler de içermektedir. Betimleyici istatistik analizleri sonucunda katılımcıların zorluk ve ilgi altboyutlarında nötür tutumlara sahip oldukları, diğer altboyutlarda ise olumlu tutumlara sahip oldukları görülmüştür. İstatistik kazanımlarının matematik başarısı, duygu, bilişsel yeterlilik, ilgi, çaba ve değer değişkenleri ile anlamlı derecede ilişkili olduğu görülmüştür. Önerilen yapısal regresyon modelini test etmek amacıyla, yapısal eşitlik modellemesi (YEM) analizi kullanılmıştır. Analiz sonucunda duygu, değer, bilişsel yeterlilik ve ilgi değişkenlerinin istatistik kazanımları üzerine toplam etki değerlerinin yüksek ve istatistiksel olarak anlamlı olduğu bulunmuştur. Matematik başarısı ve çaba değişkenlerinin istatistik kazanımları üzerine toplam etki değerlerinin küçük fakat istatistiksel olarak anlamlı olduğu görülmüştür. Öğrencilerin istatistiğin zorluğuna yönelik tutumlarının ise istatistik kazanımlarını açıklamada toplam etkisinin olmadığı bulunmuştur. Önerilen model istatistik kazanımları toplam varyansının % 66'sını istatistiksel olarak anlamlı derecede açıklamaktadır.

Anahtar Kelimeler: İstatistiğe yönelik Tutumlar, Öğrencilerin Matematik Başarıları ile ilgili Kişisel Görüşleri, İstatistik Kazanımları, Yapısal Eşitlik Modeli

In dedication to

my family & friends

for their love

In honor of

my mentors,

for their contribution

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CHAPTER I

INTRODUCTION

This chapter introduces the main problem of the study. It begins with the background of the present study followed by the purpose of the study. The chapter also includes significance of the study and definition of terms.

1.1. Background to the Study

By means of learning experiences, students are expected to know, understand, and be able to demonstrate certain skills, behaviors, and attitudes. These learning experiences have been defined and described by several different learning theories. The 20th century the most common learning theories have been behavioral and cognitive learning theories (Bigge & Shermis, 2004). Behavioral learning theorists explain learning as relatively permanent change in "hierarchical, observable, and measurable behaviors" (Ornstein & Hunkins, 1998, p.133) whereas cognitive learning theorists explain learning "as an internal change in mental associations" (Pritchard, 2008, p. 32).

Learning is not a mere acquisition of facts, it occurs in multiple dimensions (Reid & Petocz, 2004). Educational scientists leaded by Bloom (1956) categorized learning into three domains: cognitive, affective, and psychomotor. Cognitive domain involves knowledge structures and abilities, psychomotor domain deals with physical movement, coordination, and motor-area skills. Affective domain involves students' beliefs, attitudes, values, and emotions. In the taxonomy of affective domain, the learner moves from the stage of being aware of what they are learning to the stage of internalizing a value system (Krathwohl, Bloom, & Masia, 1964, as cited in Savickiene 2010). In this taxonomy, the internalization of value system is assumed to control learner's behavior. Therefore, it is assumed that affective learning has a role in guiding learners' actions. Consistently, Smith and Ragan (1999) point out that any cognitive learning has some affective component to it; and, in any level of education, students are expected to appreciate the significance of the subjects they are studying. The affective domain is the only one area that we can express this expectation (Seels & Glasgow, 1990). Cognitive learning domain has gained the most attention and has been the primary goal of education in any field. Affective domain has not gained that much attention although it has an important role and place in education.

As stated earlier, affective domain comprises several constructs such as beliefs, attitudes, and emotions. From the constructs of affective domain, attitudes have been commonly investigated in educational and psychological research. In these studies, the importance of attitudes on human behavior has been the core issue (Eagly & Chaiken, 2005). As stated by Bohner and Wanke, (2002) attitudes are important, as they are central part of human individuality. People tend to evaluate things. They love and hate, like and dislike, favor and oppose. In addition, "when individual attitudes turn into public opinion then these attitudes determine the social, political, and cultural climate in a society which in turn effects the individual lives of the people in that society" (Bohner & Wanke, 2002, p. 4).

In the context of statistics education, the place of affective domain has been no different. Students' attitudes toward statistics have a very recent research background. This is partly because of the fact that statistics education is a new research area (Shaughnessy, 2007). In the current study, as well as cognitive learning domain, the affective learning domain is of special interest, as this study primarily emphasizes on the relationship among students' attitudes toward statistics, self-reported math achievement, and statistics outcomes.

Statistics is defined as "the department of study that has for its object the collection and arrangement of numerical facts of data, whether relating to human affairs or to natural phenomena" (Oxford English dictionary, n.d.), or simply as the "science of learning from data" (Moore, 2005, p. 206). 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.

"As a society, we face many issues. Securing our global competitiveness, increasing quality and productivity, adapting to the changing composition of the workforce, overcoming population and other threats to the environment, addressing the needs of an aging population, and determining when to release new treatments for diseases are but a sample of those already before us. These and other difficult problems stand to benefit from the contributions that statisticians can make to our understanding, and from increased statistical literacy on the part of both policy makers and the public" (Wallman, 1993, p.3).

As the quotation above addresses, understanding statistics is an inevitable requisite for the individuals of developed societies. Statistics is about solving real world problems (Hand, 1998). Therefore, it is not only needed for conducting scientific research but also needed for being an informed citizen and for advancing in technology as a society. However, for many years, statistics has seen as a branch of mathematics (Greer, 2000) and the practice of statistics has been ignored by scientific community (Nelder, 1999).

Consequently, “the understanding of statistics has remained the domain of a selected few” (Lajoie, Jacobs, & Lavigne, 1995, p.401).

Students are introduced with statistics courses in universities from the beginning of the 20th century (Verhoeven, 2009). In the current study, a statistics course refers to the service course offered to undergraduate or graduate students who are not majoring in statistics. The early statistics courses had their roots in 1925 with the publication of the book “Statistical Methods for Research Workers” by R.A. Fisher. During the late 1960s and early 1970s, John Tukey’s ideas of exploratory data analysis brought revolutionary changes in statistics courses so that students started to analyze data without spending hours chained to bulky mechanical calculators (American Statistical Association, 2010). In the early practice of statistics courses, the instruction was mostly traditional. The focus was on probability theory and on specific statistics procedures. Statistics was studied from a mathematical perspective. Students were expected to memorize statistical knowledge and follow rules and procedures in standard contexts (Vanhoof, 2010).

In 1990s, statistics instruction had undergone another revolution primarily as a consequence of the inclusion of computers (Hand, 1998). Statistical software tools enhanced statistical applications and reduced the overemphasis of mathematics in statistics courses. Currently, many changes have been implemented in statistics courses as more technological devices become available for data analysis and simulations. Accordingly, the goal of statistics education tend to emphasize more on conceptual understanding and less on mechanics of the mathematical procedures (American Statistical Association, 2010).

Today, statistics courses are compulsory for most of the students from a broad spectrum of Social and Natural Sciences fields. In terms of research, studies on statistics education have started to accelerate recently. The first scientific journal which was dedicated to statistics education (Statistics Education Research Journal, SERJ) was published in 2002 (Garfield & Ben-Zvi, 2007; Ottaviani, 2005). Since then, research on statistics education had an amazing increase (Shaughnessy, 2007).

Researchers including mathematics and statistics educators, cognitive and educational psychologists, and statisticians mainly focused on students' learning in statistics and improving the cognitive side of instructions whereas little attention has been paid to the affective side of statistics instruction (Gal & Ginsburg, 1994; Shaughnessy, 2007). Majority of research covered studies on cognitive learning outcomes such as statistics achievement, statistical thinking, statistical reasoning, and statistical literacy (Gal, 2002; Garfield & Gal, 1999; Groth, 2006; Lavigne & Lajoie, 2007; Mooney, 2002; Rumsey, 2002; Tempelaar, Gijselaers, & Schim van der Loeff, 2007). In these studies, the role of cognitive and demographic factors and different instructional methods on students' attainment of cognitive learning outcomes were investigated. Results of these studies revealed positive contribution of mathematics achievement on statistics achievement (Galli, Matteo, Chiesi, & Primi, 2008; Johnson & Kuennen, 2006; Lalonde & Gardner, 1993; Nasser, 2004; Wisenbaker, Scott, & Nasser, 2000) when demographic variables such as gender had no consistent role on explaining cognitive outcomes in statistics (Brooks, 1987; Buck, 1985; Fitzgerald & Jurs, 1996; Schram, 1996). Interventions such as technology use (Christmann & Badgett, 1999; delMas, Garfield, & Chance, 1999; Liu, Lin, & Kinshuk, 2010; Summers, Waigandt, & Whittaker, 2005) and use of real-life examples enhanced cognitive learning outcomes in statistics (Derry, Levin, Osana, Jones, & Peterson, 2000; Evans, 2007; Lawson, Schwiers, Doellman, Grady, & Kelnhofer, 2003).

In addition to the research that focused on the cognitive side of statistics education, a limited number of studies were conducted on understanding students' attitudes toward statistics. Most of these studies adopted survey designs and indicated that positive attitudes toward statistics contribute to the success in statistics courses (Chiesi & Primi, 2009; Dempster & McCorry, 2009; Evans, 2007; Limpscomb, Hotard, Shelley, & Baldwin, 2002; Sizemore & Lewandowski, 2009; Sorge & Schau, 2002; Tempelaar et al., 2007).

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, Hogg, Schau, & Whittinghill, 2002; Schau, 2003). In addition to the survey studies, a limited number of experimental studies were conducted. These studies revealed that interventions such as technology use (Carlson & Winquist, 2011; Suanpang, Petocz, & Kalceff, 2004; Wiberg, 2009) and value-reappraisal strategy use (Acee & Weinstein, 2010) increased students' positive attitudes toward statistics. These studies showed that attitudes toward statistics could be improved when appropriate instructional methods are adopted.

Similar to the international literature, students' attitudes toward statistics have rarely been investigated in Turkey. Restricted number of studies revealed that attitudes toward statistics were significantly related to statistics achievement (Emmioğlu & Capa-Aydin, 2011; Emmioğlu, Capa-Aydin, & Çobanoğlu, 2010). In addition, a limited number of studies were conducted to investigate several different factors influencing students' attitudes toward statistics (Aksu & Bikos, 2002; Çalıkoğlu-Bali, 2000; Doğan, 2009; Yılmaz, 2006).

As understood from the background of the study, little attention has been given to statistics education for many years. Accordingly, research on statistics education has newly aroused interest in the scientific community (Shaughnessy, 2007). When most of the statistics education research focused on the cognitive side of statistics instruction, small but growing number of studies focused on the affective side of statistics instruction. These studies pointed out the importance of students' attitudes toward statistics and the urgent need for investigating affective factors in statistics education.

1.2. Purpose of the Study

The aim of this study is to investigate the structural relationships among mathematics achievement, attitudes toward statistics, and statistics outcomes by testing a structural model, which is called "Statistics Attitudes-Outcomes Model". The model is based on Eccles and colleagues' application of expectancy value theory of achievement motivation to the mathematics education (Eccles, 1983; Eccles & Wigfield, 1995). The model is also based on the Statistics Attitudes-Achievement Structural Model (Sorge & Schau, 2002).

The current study examines both the overall model fit and the relationships among mathematics achievement (self reported previous and overall mathematics achievement), attitudes toward statistics (affect, cognitive competence, difficulty, value, interest, effort), and statistics outcomes (total grade earned at the end of taking the statistics course, willingness to use statistics in the remainder of the degree program, and willingness to use statistics when employed). The conceptual structure of the proposed model is presented in Figure 1.1.

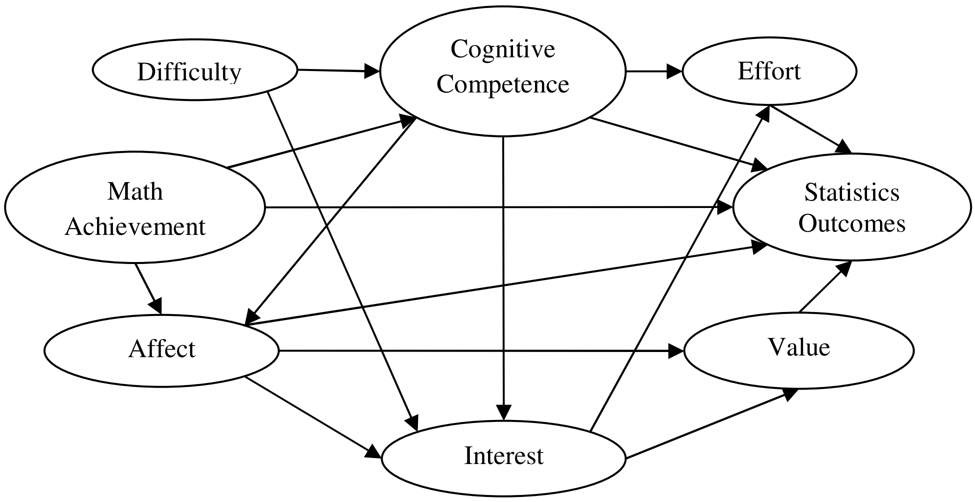


Figure 1.1 Conceptual Structure of the Statistics Attitudes-Outcomes Model

1.3. Significance of the Study

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, literature demonstrates that the current situation of statistics education is on the contrary (Garfield & Ben-Zvi, 2007). Statistics have a negative reputation among students. Students have anxiety and negative feelings about statistics (Onwuegbuzie & Wilson, 2003; Snee, 1993). Some of them even call statistics as "sadistics" (Lalonde & Gardner, 1993). Current studies suggest that statistics courses are needed to be revised in a way to motivate students to learn statistics (Carnell, 2008; Dempster & McCorry, 2009; Murtonen & Lehtinen, 2003; Wiberg, 2009). Therefore, it is highly important to conduct more research on understanding the role of attitudes in statistics education. Only by this way, it might be possible to find out why students have certain attitudes toward statistics and to suggest ways to increase and maintain students' positive attitudes toward statistics. Eventually, the quality of statistics education would increase with the help of such studies (Garfield, et al., 2002).

There have been some attempts to understand students' attitudes toward statistics but several drawbacks were evident in most of these early studies. Firstly, most of these studies were based on experiences of researchers, instead of educational and cognitive models (Bartsch, 2006; Evans, 2007; Rhoads & Hubele, 2000; 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 (Rhoads & Hubele, 2000; Schau, Stevens, Dauphinee, & Del Vecchio, 1995; Waters, Martelli, Zakrajsek, & Popovich, 1988). 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 & McCorry, 2009; Lawless & Kulikowich, 2006). This study has some characteristics, which would contribute to the present literature and the practice of teaching statistics by attempting to ameliorate some of the shortcomings mentioned above.

First, this study is based on a theoretical background. The proposed and tested structural model of the study is based on Eccles and colleagues' application of expectancy value theory of achievement motivation to the mathematics education (Eccles, 1983, 2005; Eccles & Wigfield, 2002; Wigfield, Tonks, & Klauda, 2009). It is expected that the study would contribute to the current literature by suggesting a way to apply Eccles' expectancy value model in the context of statistics education. By testing the model, it is expected that this study would contribute to the literature in general by investigating the relationships among several affective and cognitive factors in the context of statistics education. In addition, the current study would help researchers to adapt the proposed model for different subjects such as science and mathematics education.

Second, the study utilizes the most current, widely validated, and theoretically grounded instrument, Survey of Attitudes Toward Statistics-36© (SATS-36©), to assess students' attitudes toward statistics. Thus, it is expected that the current study would also contribute to the literature by using a current and widely recognized instrument.

Third, in the current study, statistics outcomes variable not only includes statistics achievement but also students' willingness to use statistics in the remainder of degree program and willingness to use statistics when employed. By this way, the current study makes an original and fundamental contribution to literature since students' attitudes are seen important for influencing students' statistical behavior after they leave the classroom (Gal, Ginsburg, & Schau, 1997).

Fourth, this study would contribute to the Turkish literature and to the practice of statistics education in Turkey. By translating and adapting SATS-36© into Turkish language and culture, researchers and statistics educators would be stimulated to investigate Turkish students' attitudes toward statistics. In addition, as there are a limited number of research studies on statistics education in Turkey, the results of the study would suggest new directions for future studies. By means of this study, it might also be possible to conduct cross-cultural comparisons between Turkish and other country samples.

The last but not the least, the current study is significant in terms of its contribution to the quantitative scientific research in general terms; because, the current study attracts attention to the importance of statistics and statistics education. It is a widely known fact that statistics is an important tool for a variety of natural science and social science disciplines. For this reason, the current study would make a significant contribution to the advancement of the analysis procedures of quantitative research in general by putting emphasis on students' attitudes toward statistics and on students' statistics outcomes.

1.4. Definition of Terms

Attitudes toward Statistics are defined as individuals' learned positive or negative responses with respect to statistics. Attitudes toward statistics is also described as a multidimensional concept that consist of affective (emotions and motivations), cognitive (beliefs about the ability to learn statistics), and behavioral (action tendencies in studying statistics) components (Coetzee & van der Merwe, 2010). 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).

Cognitive Competence is defined as students' perceptions about their intellectual knowledge and skills when applied to statistics (Schau, 2005) along with their expectancies for success in statistics (Sorge & Schau, 2002).

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 amount 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.

Statistics Outcomes are defined, in this study*,* as the students' statistics achievement levels and future use of statistics. In the current study, statistics outcomes involve three components: statistics achievement, willingness to use statistics in the remainder of the degree program, and willingness to use statistics when employed.

CHAPTER 2

REVIEW OF LITERATURE

This chapter includes a brief overview of the research and theoretical background for attitudes toward statistics. The chapter begins with brief information on attitude and attitude research in general. Next, theoretical framework for “Statistics Attitudes-Outcomes Model” is presented followed by the measures of attitudes toward statistics, review of research on attitudes toward statistics, and brief information on Statistics Attitudes-Achievement Model that the hypothesized model of the current study was based on. The chapter ends with the review of research on attitudes toward statistics in Turkey followed by a summary section.

2.1. Attitude and Attitude Research

The word “attitude” was used to describe the spatial orientation or visible position of physical objects such as statues or paintings. It derived from the Latin word “aptus” which refers to the “fitness” or “adaptedness” and to the “aptitude” that connotes a subjective or mental state of preparation for an action (Allport, 1937; Breckler & Wiggins, 1989). In psychology, the construct of attitude has not had a globally accepted definition for a long period of time; therefore, there had been little agreement on the meaning of attitude (Pratkanis, 1989). The starting point for the definition of attitude was accepted as Gordon W. Allport’s (1935) definition of attitude. He stated, “attitude is a mental and neural state of readiness, organized thorough experience, exerting a directive or dynamic influence upon the individual's response to all objects and situations with which it is related" (Allport, 1935, p.810). More recently, attitude was defined as "a disposition to respond favorably or unfavorably to an object, person, institution or an event" (Ajzen, 2005, p.3), or as "learned cognitive, affective and behavioral predispositions to respond positively or negatively to certain objects, situations, institutions, concepts or persons" (Aiken, 2002, p.3). As understood from these definitions, one important characteristic of attitudes is that attitudes are evaluative, they are expressed in evaluative terms as favorably or unfavorably (Eiser & van der Pligt, 1988). Another important point is that attitude is a multidimensional construct that includes cognitive, affective and behavioral components (Aiken, 2002).

Attitudes have been studied for over a hundred year (Ostrom, 1989). In the early years, attitude research was seen as a distinctive field, even that the social psychology was called as the scientific study of attitudes (Wallace, Paulson, Lord, & Bond Jr., 2005). The two decades between 1930 and 1950 was accepted as the beginning of extensive empirical and theoretical studies of attitudes (Ostrom, 1968). From the beginning of the attitude research, prediction of behavior has always been a core issue in the study of attitudes (Eagly & Chaiken, 2005) and attitudes have been assumed to be related with behaviors (Holland, Verplanken, & Van Knippenberg, 2002). The traditional way of looking at the attitude-behavior relationship was that attitudes cause behaviors (Eiser & van der Pligt, 1988). Despite the fact that the view "attitudes cause behaviors" was abandoned by some of the current researchers, the assumption that there is a relationship between attitudes and behaviors has been widely accepted until present. An everyday example to this assumption is that huge amount of money has been invested on advertisements because of the belief that consumers' attitudes toward a commercial product influence their decisions to purchase the product (Maio & Haddock, 2004). From a more scientific perspective, several meta-analysis studies were conducted to test the relationships between attitudes and behaviors. These studies reported a moderate and statistically significant relationship, r = .30 to .41, between attitudes and behavior (Kraus, 1995; Wallace, Paulson, Lord, & Bond Jr., 2005). From the theoretical perspective, several theories have focused on the role of attitudes on explaining human behaviors. These theories include social cognitive theory, self-efficacy and self-determination theories, self-regulation theories, interest theories, control theory, attribution theory, goal theories, and expectancy value theories.

In sum, attitude is a multidimensional construct that involves individuals' positive or negative dispositions toward certain objects or situations. It has been studied for many years in education and psychology in which the relationship between attitudes and behavior has been the core issue. Many of these empirical and theoretical studies suggested that attitudes play important roles in human behavior.

2.2. A Theoretical Framework for the "Statistics Attitudes-Outcomes Model"

As mentioned above, many theories have attempted to explain the relationship between individuals' attitudes and behaviors. Being focused on the relationships among students' attitudes toward statistics, mathematics achievement, and statistics outcomes, the "Statistics Attitudes-Outcomes Model" is congruent with several theories. Presenting all of these theories is beyond the scope of this study. However, it is beneficial to provide brief information about the major theories that form the basis of "Statistics Attitudes-Outcomes Model."

Learning Theories A learning theory is defined as a "systematic integrated outlook in regard to the nature of the process whereby people relate to their environments in such a way as to enhance their ability to use both themselves and their environments in a most effective way" (Bigge & Shermis, 2004, p.3). There are as many learning theories as theorists (Kiesler, Collins, & Miller, 1969). However, it is possible to classify the twentieth century learning theories into two broad families: behavioral and cognitive learning theories (Bigge & Shermis, 2004). These theories explain the role of attitudes on human learning from different point of views. Although behavioral learning theories do not deny the affective dimension of learning, their justification is implicit. They propose that the behaviors that have been reinforced or rewarded in the future are likely to be repeated. This postulate that individuals' readiness and willingness should be ensured before they learn. In a different way, cognitive learning theories explicitly emphasize the role of attitudes on learning. In cognitive learning theories, not only students' learning information but also their attitudes are important. For example, cognitive learning theories such as Bandura's social cognitive theory contends that students' goals, expectations, and competence are the important factors influencing their performance and developmental status (Schunk, 2008). In sum, different learning theories deal differently with the status of attitudes in learning. However, all of them emphasize the significance and the need for having positive attitudes toward the process of learning and toward the subject learned.

"Statistics Attitudes-Outcomes Model" is congruent with learning theories because it assumes that beside cognitive factors (mathematics achievement in "Statistics Attitudes-Outcomes Model"), affective factors (attitudes toward statistics in "Statistics Attitudes-Outcomes Model") play important role in students' attainment of learning objectives (statistics outcomes in "Statistics Attitudes-Outcomes Model").

Self-Efficacy Theory assumes that individuals' judgment of their efficacy is a function of the task, situational characteristics operating at the time, their prior experience and beliefs about the task, and their current beliefs and feelings as they work on the task (Pintrich, 2003). In other words, individuals' perceived self-efficacy is influenced by four determinants. These are (1) previous performance accomplishments which is based on personal mastery experiences, (2) vicarious experiences of observing others succeed through their efforts, (3) verbal encouragement by others, and (4) ones' physiological reactions from which people judge their level of anxiety and vulnerability to stress (Bandura & Adams, 1977; Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2006). The theory postulates that individuals who have self-efficacy work harder and persist longer when they meet difficulty than those who do not (Schunk, 1991). The self-efficacy theory also postulates that self-efficacy is not the sole determinant of behavior. It hypothesizes that "given appropriate skills and adequate incentives, efficacy expectations are a major determinant of people's choice of activities, how much effort they will expend, and of how long they will sustain effort in dealing with stressful situations" (Bandura, 1977, p. 194). In sum, self-efficacy theory proposes that people who have the necessary skills and the reasons to perform well and think that they can perform well do better than people who think that they will fail on a task (Bandura, 1977; Gist & Mitchell, 1992).

In "Statistics Attitudes-Outcomes Model", students' perceptions about their capabilities in statistics are represented by cognitive competence variable. In the model, students' perceptions about the difficulty of statistics and their self-reported mathematics achievement are the determinants of cognitive competence. From this perspective, "Statistics Attitudes-Outcomes Model" is consistent with the proposal of self-efficacy theory that individuals' self-efficacy is a function of their prior beliefs about the task and their experience. In addition, "Statistics Attitudes-Outcomes Model" is consistent with self-efficacy theory as it suggests that when students have high self-efficacy they spend effort to work hard and they have higher achievement. Moreover, like self-efficacy theory, the "Statistics Attitudes-Outcomes Model" regards not only students' cognitive competence but also incentives such as students' interests, affect and value toward statistics.

Self-Determination Theory assumes that all individuals have natural, innate and constructive tendencies to develop a unified sense of self (Deci & Ryan, 2002). In other words, the theory views human beings as "proactive organisms whose natural and intrinsic functioning can be either facilitated or impeded by the social context" (Deci, Eghrarl, Patrick, & Leone, 1994). Thus, individuals are assumed to involve both autonomy (inner organization and self-regulation) and homonomy (integration of oneself with others). The theory suggests that healthy development involves the complementary functioning of these two aspects. Self-determination theory has focused on the factors that enhance or undermine the natural processes of self-motivation. After conducting research on investigating these factors, the proponents of the self-determination theory proposed that contexts supportive of three human needs (autonomy, competence, and relatedness) foster greater self-motivation than contexts that thwart satisfaction of these needs (Ryan & Deci, 2000). Therefore, self-determination theory posits that an understanding of human motivation requires the consideration of psychological needs for competence, autonomy and relatedness (Deci & Ryan, 2000; Deci, Vallerand, Pelletier, & Ryan, 1991). In this theory, competency refers to "feeling effective in one's ongoing interactions with the social environment and experiencing opportunities to exercsise and express own capacities". Relatedness is defined as "the tendency to connect with and accepted by others". Autonomy is defined as "being the perceived origin of one's own behavior which acts from interest and integrated values" (Deci & Ryan, 2002, pp.7-8). The theory suggests that the identification of these three needs is significant for individuals who wish to motivate others in a way that engenders commitment, effort and high performance (Ryan & Deci, 2000). In sum, Deci and Ryan's self determination theory postulates that individuals' behavior is self determined by promoting their (1) autonomy, which derive from their interest and valuing, (2) confidence in their own capacities, and (3) relatedness to their social environments (Deci et al., 1991). The theory suggests that when individuals are self-determined they tend to be psychologically healthier and intrinsically motivated (Wigfield et al., 2006).

"Statistics Attitudes-Outcomes Model" is consistent with self-determination theory as the theory suggests that students are expected to spend effort and to have higher achievement when they have confidence and autonomy. In other words, "Statistics Attitudes-Outcomes Model" is consistent with self-determination theory with regard to focusing on students' cognitive competence, personal interest and valuing of the task for achieving the desired goals.

The Theory of Planned Behavior asserts that the immediate cause of a behavior is behavioral intention. According to this theory, the three determinants of behavioral intentions are attitudes toward the behavior, subjective norm and perceived behavioral control (Bohner & Wanke, 2002). In this theory, attitudes toward the behavior are the degree to which a person has a favorable/unfavorable evaluation of the behavior. Subjective norm is the perceived social pressure to perform or not to perform the behavior. Perceived behavioral control is the self-efficacy with respect to the behavior. Behavioral intention refers to the effort individuals are planning to exert in order to perform the behavior (Ajzen, 1991). To this theory, the more favorable the attitudes, the perceived behavioral control and the subjective norm with regard to the behavior, the stronger should be an individual's intention to perform the behavior (Ajzen, 2005).

"Statistics Attitudes-Outcomes Model" and the theory of planned behavior share similar constructs. In theory of planned behavior, the focus is on individuals' attitudes toward any behavior whereas "Statistics Attitudes-Outcomes Model" specifically focuses on students' attitudes toward statistics. Cognitive competence in Statistics Attitudes-Outcomes model refers to students' perceptions about their intellectual knowledge and skills when applied to statistics (Schau, 2005). Similarly, in theory of planned behavior, perceived behavioral control refers to the self-efficacy with respect to the behavior. In theory of planned behavior, behavioral intention refers to the effort individuals are planning to exert in order to perform the behavior. Likewise, in "Statistics Attitudes-Outcomes Model", effort refers to the amount of work students spend to learn statistics (Schau, 2005). Lastly, Statistics Attitudes-Outcomes Model focuses on statistics outcomes as the ultimate behavior. The components of the theory of planned behavior and the corresponding components of the "Statistics Attitudes-Outcomes Model" are presented in Table 2.1.

Table 2.1

Corresponding Components of "Statistics Attitudes-Outcomes Model" to the Theory of Planned Behavior

Components of "Statistics Attitudes-Outcomes Model"	Components of The Theory of Planned Behavior
Attitudes toward statistics	Attitude toward the behavior
Cognitive competence	Perceived behavioral control
Effort	Behavioral intention
Statistics outcomes	Behavior

As seen in Table 2.1, "Statistics Attitudes-Outcomes Model" is congruent with the theory of planned behavior. First, the theory of planned behavior suggests that perceived behavioral control is the determinant of individuals' behaviors and behavioral intentions. Similarly, in "Statistics Attitudes-Outcomes Model" students' cognitive competence in statistics is a determinant of students' statistics outcomes and the effort they spend to learn statistics. Second, the theory of planned behavior suggests that behavioral intention is the immediate cause of a behavior. In a similar point of view, in "Statistics Attitudes-Outcomes Model", the effort students spend to learn statistics is related to their statistics outcomes.

The Eccles' et al. Expectancy-Value Model of Achievement Performance and Choice (which is called Eccles' Model throughout the remainder of this study) is one of the most influential theories on explaining individuals' nature of achievement performance and achievement related choices (Wigfield & Eccles, 2002). Eccles and her colleagues developed their model based on expectancy value theory and applied it to the mathematics education (Eccles, 1994; Wigfield & Eccles, 2000, 2002). Expectancy value theory proposes that individuals' expectancies for success and the subjective value they attach for succeeding are important determinants of individuals' motivation to perform different achievement tasks; their choices of which tasks to pursue, and their persistence and performance (Atkinson, 1957; Denissen, Zarrett, & Eccles, 2007; Eccles, 1994; Wigfield & Eccles, 2000, 2002).

"Expectancy of success" is defined as a cognitive anticipation that performance of some act is followed by a particular consequence (Atkinson, 1957). Similarly, expectancies were also defined as the beliefs about how one will do on upcoming tasks or activities either in the immediate or longer-term future (Eccles, 1983; Eccles & Wigfield, 2002; Wigfield & Eccles, 2002). Atkinson (1957) defined "value" as the relative attractiveness of succeeding or failing on a task. Eccles and Wigfield (2002) defined subjective task values as how a task meets different needs of individuals. They conceptualized subjective task values in four components: attainment value, intrinsic value, utility value, and cost (Eccles, 1994; Wigfield & Eccles, 2000, 2002; Wigfield, Tonks, &

Klauda, 2009). The comparison of the corresponding components of "Statistics Attitudes-Outcomes Model" is presented in Table 2.2 followed by the explanation of the comparison of two models.

Table 2.2

Corresponding Components of "Statistics Attitudes-Outcomes Model" to Eccles' Model

"Statistics Attitudes Outcomes Model"	Eccles' Model
- Mathematics achievement	- Previous achievement related experiences
- Affect	- Affective memories & Intrinsic value
- Cognitive competence	- Self-concept of one's abilities & Expectation of success
- Value	- Attainment value & Utility value
- Difficulty	- Perception of task demand
- Interest	- Interest-enjoyment value
- Effort	- Cost
- Statistics outcomes	- Achievement related choices and performance

Eccles' Model hypothesizes that individuals' performance and achievement related choices are directly influenced by their expectancies for success and the subjective value that they attach for succeeding (Atkinson, 1957; Denissen, Zarrett, & Eccles, 2007; Eccles, 1994; Wigfield & Eccles, 2000; 2002; Wigfield, Tonks, & Klauda, 2009). In other words, their model suggests that individuals select the tasks for which they have the highest expectations for success and to which they attach the greatest subjective task value (Denissen, Zarrett, & Eccles, 2007). Eccles' Model proposes that students' expectancies for success and subjective task values are influenced by other achievement related beliefs (achievement goals, self-schemata, and task specific beliefs). These beliefs are influenced by interpretations of previous performance, interpretations of other's attitudes and expectations, and memories of similar tasks. The model also links these beliefs to various other contextual and cultural influences such as cultural norms, experiences, aptitudes, personal beliefs, and attitudes (Eccles, 1994; Wigfield & Eccles, 2000; 2002). The model is demonstrated in Figure 2.1.

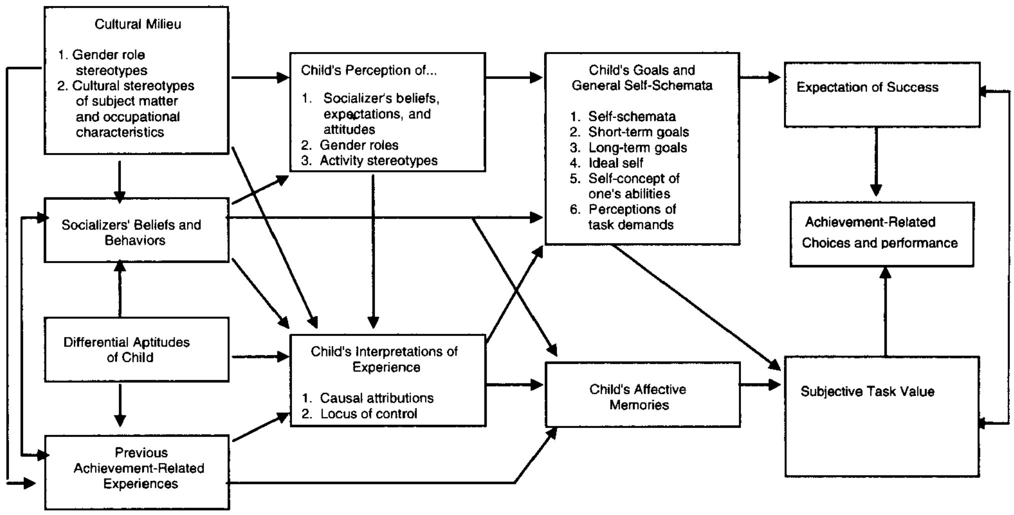


Figure 2.1 Eccles' Expectancy-Value Model of Achievement Performance and Choice (*Source:* Wigfield et al., 2009. Reprinted with permission from the publisher).

In the current study, Eccles' Model is adopted as a main theoretical framework primarily for two reasons. First, the expectancy value theory is one of the most comprehensive theories that can be used to explain the role of attitudes on understanding students' academic behaviors in statistics (Ramirez, Emmioglu, & Schau, 2010; Schau, 2003). Second, the Survey of Attitudes toward Statistics-36©, (SATS-36©) which is based on expectancy value theory (Schau, 2003; Tempelaar et al., 2007) was utilized in this study. Although Eccles' Model and "Statistics Attitudes-Outcomes Model" has essential similarities, these two models have some differences. These differences along with their reasons are the following:

1. Previous achievement related experiences component in Eccles' Model is represented by mathematics achievement (self-reported past and overall mathematics achievement) component in "Statistics Attitudes-Outcomes Model".

2. In Eccles' Model, individuals' perception of task demand is conceptualized as the difficulty of the subject for a specific student; however, in "Statistics

Attitudes-Outcomes Model”, difficulty is defined as the students’ attitudes toward the difficulty of statistics as a subject for general people (Schau, 2003).

3. Self-concept of one’s abilities and expectation of success components in Eccles’ Model are combined into cognitive competence component in “Statistics Attitudes-Outcomes Model”. The reason for this modification is that Eccles and her colleagues reported that these two constructs cannot be distinguished empirically (Denissen et al., 2007; Eccles, O’Neill, & Wigfield, 2005; Eccles & Wigfield, 1995; Wigfield & Eccles, 2000).

4. The two dimensions of Eccles’ subjective task value, attainment value and utility value, are combined into one value component in “Statistics Attitudes-Outcomes Model” as individuals’ views of the importance and usefulness of the statistics are measured by the value subscale of SATS-36© in the current study.

5. In Eccles’ model, subjective task value component involves intrinsic value, cost, and attainment and utility value constructs. In “Statistics Attitudes-Outcomes Model”, effort (similar to cost variable in Eccles Model), value, and interest variables are represented as distinct constructs. Intrinsic value and affective memories components of Eccles’ Model are represented by Affect component in “Statistics Attitudes-Outcomes Model”. The reasons for separating these constructs is that it is confirmed by the existing empirical studies that affect, value, interest and effort are empirically distinct constructs (Hilton et al., 2004; Schau et al., 1995; Tempelaar et al., 2007; Verhoeven, 2009). In addition, these constructs are theoretically distinct as summarized previouslt in the theoretical background of the “Statistics Attitudes-Outcomes Model”.

Based on Eccles' Model, the "Statistics Attitudes-Outcomes Model" has many aspects that are similar to Eccles' Model especially with regard to the relationships that they suggest. These similarities are presented as the following:

1. In Eccles' Model, it is assumed that previous achievement related experiences impact students' affective memories which affect students' subjective task values attributed to the achievement choices. In addition, it is proposed that subjective task values affect students' achievement choices and performances. Similarly, "Statistics Attitudes-Outcomes Model" proposes that mathematics achievement (self reported past and general math achievement) is directly related to students' affect toward statistics, which in turn is directly related to students' perception about the value of statistics and their personal interest in statistics. Statistics Attitude-Outcomes Model also assumes that students' perceptions about the value of statistics are directly related to statistics outcomes.

2. In Eccles' Model, students' expectancies of success are influenced by their perceptions of task demands. Similarly, in "Statistics Attitudes-Outcomes Model", it is proposed that students' perceptions about the difficulty of statistics is directly related to the students' cognitive competence in statistics.

3. In Eccles' Model, it is proposed that individual's perception of task demands influence their interest-enjoyment value. Similarly, in "Statistics Attitudes-Outcomes Model", it is proposed that students' perceptions of the difficulty of statistics is directly related to students' personal interest in statistics.

4. In Eccles' Model, it is proposed that individuals' self-concept of abilities impacts their perceptions of the amount of cost that is to be taken for accomplishing the task which in turn impact individuals' achievement choices and performances. Similarly, in "Statistics Attitudes-Outcomes Model", it is proposed that students' cognitive competence in statistics is directly related to the effort they spend to learn statistics, which in turn is directly related to the statistics outcomes.

Overall, "Statistics Attitudes-Outcomes Model" is congruent with Eccles' application of expectancy value theory. Because, "Statistics Attitudes-Outcomes Model" assumes that students' mathematics achievement, perceptions of their ability for learning and doing statistics, their perceptions about the difficulty of statistics, their affect toward statistics, their personal interest in statistics, the effort they spend to learn statistics, and their valuing of statistics are the important factors for explaining students' statistics outcomes.

2.3. Measures of Attitudes Toward Statistics

"It will be conceded at the outset that an attitude is a complex affair which cannot be wholly described by any single numerical index" (Thurstone, 1928, p.530).

Although attitudes are routinely represented by a single numerical index; social scientists have long recognized that this practice is insufficient to capture all relevant properties of attitudes (Fabrigar, MacDonald, & Wegener, 2005). Attitude is a hypothetical construct which is inaccessible to direct observation and should be inferred from measurable responses (Ajzen, 2005). Since Thurstone (1928) declared that attitudes could be measured, attitude instruments have started to be developed alongside the different conceptual definition of attitudes. In these instruments, researchers primarily have focused on explicit self-reports and the evaluative feature of attitudes (Vargas, 2004).

In terms of statistics attitudes, a number of instruments have been developed to assess students' attitudes toward statistics starting from 1980s. Similar to the earlier attitude instruments, most of the statistics attitudes instruments focused on self-reports and evaluate characteristic of attitudes. However, these instruments are inconsistent in terms of the multidimensionality of attitudes. They have diverse viewpoints in terms of the number and content of the components that comprise students' attitudes toward statistics as explained below. The instruments that attempts to measure students' attitudes toward statistics include Statistics Attitudes Survey (Roberts & Bilderback, 1980), Attitudes Toward Statistics (Wise, 1985), Multi-factorial Scale of Attitudes Toward Statistics (Auzmendi, 1991), and Students Attitudes Toward Statistics (Sutarso, 1992). These instruments are presented in Table 2.3 along with their components and internal consistency values represented by Cronbach alpha coefficients.

Table 2.3

Some Examples of the Early Attitudes Toward Statistics Measures

Instruments	Components	Cronbach alpha
SAS: Statistics Attitudes Survey (Roberts & Bilderback, 1980)	One component	.90-.95
ATS: Attitudes Toward Statistics: (Wise, 1985)	Course, Field	1. .90 2. .92
MSATS: Multi-factorial Scale of Attitudes Toward Statistics (Auzmendi, 1991)	Motivation, Enjoyment, Anxiety, Confidence, Usefulness	.60- .87
STATS: Students Attitudes toward Statistics (Sutarso, 1992)	Students' interest and future applicability, Relationship and impact of the instructor, Attitude toward statistical tools, Self-confidence, Parental influence, Initiative and extra effort in learning statistics	.86 (for overall scale)

The most commonly used attitudes toward statistics instruments were Statistics Attitudes Survey (Roberts & Bilderback, 1980), Attitudes toward Statistics

(Wise, 1985), and Survey of Attitudes toward Statistics© (SATS©, Schau et al., 1995). As far as is known, Statistics Attitudes Survey (SAS) was the first instrument developed to measure attitudes toward statistics. It is a one-dimensional, five-point Likert-type scale with 33 items. The reliability coefficients were reported as ranging from .90 to .93 when the instrument was administered to graduate students taking introductory statistics courses (Roberts & Bilderback, 1980; Roberts & Reese, 1987; Roberts & Saxe, 1982). Although SAS has been widely used, some problems have been reported about the content and internal structure of the survey. Some of these problems can be listed as following: the instruments' assumption that attitudes are one-dimensional, some items measure students' knowledge of statistics rather than their attitudes, and the instrument is not suitable for the administration at the beginning of a statistics course (Gal & Ginsburg, 1994; Rhoads & Hubele, 2000; Schau, 2003; Waters et al., 1988; Wise, 1985).

Five years after the development of SAS, Wise (1985) developed his Attitudes toward Statistics (ATS) scale. Like SAS, this instrument had a five-point Likert-type scale. It consisted of 29 items with two components: attitudes toward statistics course and attitudes toward statistics field. Wise (1985) reported reliability coefficients as .92 for field and .90 for course subscales, which indicated that he had highly reliable scores when the instrument was administered to the sample of introductory educational statistics students (n=92). Although Wise (1985) developed his instrument to solve the problems voiced for SAS, his instrument was also criticized in recent studies. Some of these studies argued that the field and course components of ATS did not cover attitudes toward statistics construct and this two component structure had not been validated appropriately (Gal & Ginsburg, 1994; Schau, 2003; Schau et al., 1995).

In sum, the early statistics attitudes instruments along with the mostly used ones had high internal consistency values in several studies. However, these instruments were not conclusive in terms of their subscales. There was no consistency on the components of the instruments that attempt to measure students' attitudes toward statistics. Moreover, the development of the early statistics attitude measures was not based on solid theoretical background. This is a very important point to mention as it caused problems for comparing research that conducted with different measures assessing different components of statistics attitudes. Therefore, there existed a need for the development of a new instrument, which would have a strong theoretical background and well defined components with an acceptable factorial structure.

Schau et al. (1995) suggested that a statistics attitude survey should have several characteristics. Some of these characteristics were that the scale should include the most important dimensions of attitudes, it should be applicable to different statistics courses, it should involve students' input during the survey development process, and its content validity and internal structure should be supported through confirmatory analysis techniques. Schau, et al. (1995) argued that none of the existing statistics attitude surveys had all of these characteristics. Therefore, they developed Survey of Attitudes toward Statistics© (SATS©) to include these characteristics.

Survey of Attitudes toward Statistics© (SATS©) has a seven-point response scale (1=strongly disagree, 4= neither disagree nor agree, 7= strongly agree) in which higher scores corresponds to positive attitudes (Appendix A). The survey is available in pre and post versions to measure attitudes toward statistics at the beginning and at the end of the course. The survey was initially developed with 28 items assessing four components: affect, value, cognitive competence and difficulty. More recently, two other components: effort and interest were added to the instrument based on Eccles' expectancy value theory

(Schau, 2003). Hence, the current Survey of Attitudes toward Statistics-36© (SATS-36©) yields six components with 36 items. In addition to the 36 items, SATS-36© includes items that assess other constructs such as students' characteristics and previous achievement in mathematics.

SATS-28© and SATS-36© have been used in a number of studies that involved samples with different educational levels, majors and nationalities (Barkatsas, Gialamas, & Bechrakis, 2009; Chiesi & Primi, 2009; Coetzee & van der Merwe, 2010; Tempelaar et al., 2007; Verhoeven, 2009). These studies exhibited that the survey has good psychometric properties.

The six-factor structure of the SATS-36© has been validated with maximum likelihood confirmatory factor analysis techniques and the results demonstrated a very good fit of the data to the hypothesized six-factor model (Tempelaar et al., 2007; Verhoeven, 2009). Similarly, the internal consistency values for the six components of SATS-36© exhibited high values. Cronbach alpha coefficients were reported as the following: affect = .80-.82, cognitive competence = .77-.85, value = .78-.88, difficulty = .68-.79, interest= .80-.90, effort .76-.80 (Carnell, 2008; Tempelaar et al., 2007; Verhoeven, 2009). The Cronbach alpha values that are calculated in some of the current studies were presented in Table 2.4.

Table 2.4

Comparison of Cronbach Alpha Values of SATS-36© Subscales in Different Studies

	Tempelaar et al., 2007	Carnell, 2008	Verhoeven, 2009
Affect	.82	.81	.80-.82
Cognitive Competence	.78	.85	.77-.82
Value	.78	.88	.78-.82
Difficulty	.68	.79	.71-.75
Interest	.80	.90	.83-.84
Effort	.76	.79	.80

As seen in Table 2.4, difficulty subscale had the lowest Cronbach alpha values in all of the three studies. Interest subscale had the highest Cronbach alpha values in Carnell (2008) and Verhoeven's (2009) studies, whereas Affect subscale had the highest Cronbach alpha value in Tempelaar et al.'s (2007) study.

2.4. Review of Research on Attitudes Toward Statistics

Studies on statistics attitudes can be categorized as correlational, longitudinal, and experimental with regard to their research designs. In addition, structural models were tested to examine the structural relationships among several attitudes toward statistics variables and statistics outcomes. In this section, a brief description was given to describe the current literature on statistics attitudes followed by the national literature involving statistics attitudes research conducted in Turkey.

2.4.1. Correlational Studies

Several studies have been conducted to examine the correlates of attitudes toward statistics. Some of the early studies investigated the relationship between attitudes toward statistics and statistics achievement. In 1954, Bendig and Hughes conducted a study with two samples of 50 and 71 students. They reported that attitudes toward statistics accounted for four to five percent of variability in students' statistics achievement. Twenty-four years later, Feinberg and Halperin (1978) supported their findings with a sample of students ($n = 278$) enrolled in introductory statistics courses. They found that course performance was positively correlated with students' attitudes toward quantitative subjects and negatively correlated with state-trait anxiety. Taken together, these early studies demonstrated the existence of positive relationships between attitudes toward statistics and statistics achievement.

The correlational studies on students' attitudes toward statistics were accelerated during the past twenty years. The recent research that focused on the relationship between attitudes toward statistics and achievement in statistics mostly resulted in statistically significant and positive correlations. For example, Perney and Ravid (1990) found that master degree education disciplines students' (n = 68) course performance was significantly correlated with their previous attitudes toward statistics courses, but not with attitudes toward the statistics field. Likewise, Vanhoof et al. (2006) reported positive correlations between attitudes toward statistics as a course and short term statistics exam results when they collected data from education disciplines students (n = 72) in Belgium. At the same year in United States, Lawless and Kulikowich (2006) supported previous studies. They collected data from undergraduate and graduate students (n = 267) and found positive and statistically significant relationship between students' interest in statistics and statistics knowledge. Collecting data from Italian education context, Chiesi and Primi (2010) supported the previously mentioned studies. They reported statistically significant relationship between psychology students' (n = 487) statistics achievement and attitudes toward statistics (assessed by cognitive competence, difficulty, value, and affect). At the same year in United Kingdom, Dempster and McCorry (2009) found similar results. They reported that students' (n = 154) statistics achievement was significantly related to their attitudes toward statistics (assessed by affect, cognitive competence, and value). The correlational studies also revealed that attitudes toward statistics were related to mathematics achievement. For example, Mills (2004) collected data from undergraduate students (n = 203) and reported that students who believed that they were good at mathematics significantly reported that they could learn statistics, they like statistics, and they were not scared by statistics. Coetzee and van der Merwe (2010) supported her study with a sample of South African undergraduate students (n = 235). They found statistically significant relationship between students' attitudes toward statistics and students' perceptions of how well they did in high school mathematics and students' perceptions of their current success in mathematics.

In sum, the results that are combined from early and resent literature demonstrate that attitudes toward statistics are related to statistics achievement and mathematics achievement.

2.4.2. Non-Experimental Pre-test Post-test Design Studies

There are a limited number of pretest-posttest design studies on attitudes toward statistics. These studies investigated the change in students' attitudes toward statistics before and after taking a statistics course (Evans, 2007; Limpscomb, Hotard, Shelley, & Baldwin, 2002; Schau & Emmioğlu, 2011; Sizemore & Lewandowski, 2009; Tempelaar & Schim van der Loeff).

In a research article by Evans (2007), no change from 115 students' pre attitudes toward statistics to post attitudes toward statistics was reported when students were enrolled in introductory level undergraduate statistics courses. This finding was partially supported by Sizemore and Lewandowski (2009) who reported no change between undergraduate psychology students' (n = 92) attitudes toward statistics from the beginning to the end of a statistics course, but a decline in students' scores on the perceived utility of research and statistics. Contrarily, in a study with sophomore level business students (n = 97), Limpscomb et al. (2002) found that students' cognitive competence and affect toward statistics increased from pre-test to post test. However, they supported previously mentioned studies in a way that students' scores of the value of statistics and difficulty of statistics subscales did not change from the beginning to the end of the semester. More recently, Schau and Emmioğlu (2011) investigated the changes in students' attitudes toward statistics after taking introductory statistics courses. Their sample ranged from n = 1454 to n

= 1902 depending on the six components of attitudes toward statistics being examined (affect, cognitive competence, difficulty, interest, effort, value). They found that, at the beginning of taking statistics courses, students had neutral or positive attitudes toward statistics. In their study, students maintained or decreased their attitudes toward statistics at the end of taking statistics courses. Schau and Emmioğlu (2011) reported that students valued statistics less, put less effort in statistics and were less interested in statistics at the end of taking statistics courses. Similarly, Tempelaar and Schim van der Loeff (2011) investigated the change in students' attitudes toward statistics. Their study was conducted with first year Economics and Business students (n = 3500) in Netherlands. They found that students' attitudes toward statistics declined for five components of attitudes toward statistics (affect, cognitive competence, difficulty, interest, effort) when students' attitudes toward the value of statistics stayed about the same at the end of taking statistics courses.

In summary, pre-test post-test design studies demonstrated that, overall, taking traditional statistics courses are not always enough to increase students' attitudes toward statistics from the beginning to the end of the course. Moreover, they are not always enough to, even; maintain the students' level of attitudes toward statistics.

2.4.3. Experimental Studies

A small number of experimental studies have investigated the effects of various instructional methods on students' attitudes toward statistics. Some of these methods included online and computer based instruction, value-reappraisal intervention, project based instruction and student centered instruction. One of these studies was conducted by Suanpang, Petocz and Kalceff (2004). The focus of the study was to investigate the effect of online instruction on students' attitudes toward statistics. The sample consisted of online (n = 112) and traditional group (n = 118) students enrolled in business statistics classes. Results revealed that attitudes toward statistics scores (affect, value, cognitive competence, and difficulty) of the online group increased while the traditional group remained in the same level in terms of affect, cognitive competence and value. They even scored lower in terms of the difficulty of statistics. The result indicated that online instruction helped students to have more positive attitudes toward statistics. With a similar approach, Wiberg (2009) revised a statistics course for psychology students and investigated the difference between traditional (n = 20) and revised course (n = 24) students' attitudes toward statistics. The revised course included a course web page, computer based assignments, and a problem based teaching techniques based on student centered learning. She reported that students in the revised group showed significantly higher cognitive competence in statistics, and value and affect toward statistics; whereas students' attitudes toward the difficulty of the statistics is almost the same in two groups.

Contrarily to the previously mentioned experimental studies, Carnell (2008) did not find significant difference between experimental group (n = 24) and control group (n = 18) students' attitudes toward statistics when she investigated the effect of using student data collection projects. However, she pointed out the potential presence of several confounding variables. She argued that this one study did not find any mean difference did not mean that data collection projects do not enhance attitudes toward statistics. Therefore, more studies needed to be done in order to understand the effects of using such projects on students' attitudes toward statistics.

Recently, Acee and Weinstein (2010) investigated the effect of value-reappraisal intervention on students' attitudes toward statistics. The value-reappraisal intervention involved the online presentation of messages about the importance of and potential value of statistics. Results revealed that students' attitudes toward statistics (measured by task value, interest, and endogenous instrumentality) scores in value-reappraisal group (n = 41) was significantly higher than the control group (n = 41) students. Similarly, Posner (2011) found promising results. He investigated the effects of the proficiency based assessment and re-assessment of learning outcomes (PARLO) system on students' attitudes toward statistics. The sample of his study consisted of undergraduate students of introductory statistics courses in the Eastern United States ($n_{exp.}$ = 30, $n_{cont.}$ = 31). He found that experimental group showed significantly more positive attitudes than the control group in terms of all six components of attitudes toward statistics (difficulty, cognitive competence, value, interest, effort, affect).

In summary, the effect of using nontraditional instructional methods in statistics courses on students' attitudes toward statistics was investigated in a limited number of studies. These studies suggest that using different methods in statistics instruction can enhance positive attitudes toward statistics. However, additional studies are required in order to understand the effect of using different instructional methods on students' attitudes toward statistics.

2.4.4. Structural Equation Models

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. A summary of the areas that are most relevant to this study are presented below.

As far as is known, the first statistics attitude-achievement model was developed by Lalonde and Gardner (1993). They conceptualized the learning of statistics as analogous to the learning of a language. Accordingly, they based their structural model on a theory of language learning. They reported statistically significant impact of mathematical aptitude, attitudes toward statistics, and effort on students' statistics achievement. In a similar approach, Onwuegbuzie (2003) developed his model based on foreign language learning theory for predicting statistics achievement. He collected data from graduate level education disciplines students (n = 130) and reported that statistics anxiety and achievement expectation played a central role in the model, mediating the relationship between statistics achievement and the following variables: research anxiety, study habits, course load, and the number of statistics courses taken. Harlow, Burkholder and Morrow (2002) supported the earlier studies. Their sample consisted of psychology students (n = 129) and they reported statistically significant impact of math skills and attitudes toward statistics on statistics achievement. Collecting data from Arabic speaking pre-service teachers in Israel (n = 162), Nasser (2004) also contributed previous studies that 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. Another model testing study was conducted by Bude´ et al. (2007). They hypothesized a model based on attribution and learned helplessness theories. Collecting data from first year Health Sciences students (n = 94), they reported that students' outcome expectancy scores are significantly correlated with affect toward statistics which is significantly correlated with statistics achievement. More recently, Chiesi and Primi (2010) investigated the structural relationships among mathematics background, mathematics knowledge, statistics anxiety, attitudes toward statistics and statistics achievement. Their sample consisted of undergraduate psychology student (n = 487) enrolled in statistics courses in a university in Italy. They found statistically significant direct effect of attitudes toward statistics and mathematics knowledge on statistics achievement.

In addition to 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©) to collect data from business (n = 842) and economics students (n = 776) in Netherlands. 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 summary, there have been a number of structural equation model studies 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.

2.5. Statistics Attitudes-Achievement Model

Sorge and Schau (2002) developed and tested a "Statistics Attitudes-Achievement Model" that is primarily based on Eccles and colleagues' expectancy value model. They investigated the interrelationships of students' prior academic success (gpa and mathematics achievement), attitudes toward statistics (difficulty, cognitive competence, affect, value), and achievement levels in introductory statistics and probability courses. Their sample consisted of undergraduate engineering students (n = 264). In order to collect data, they used Survey of Attitudes toward Statistics© for Engineers (SATS-E©) which was modified from SATS©-28©. They reported that previous success had a large total affect on achievement. Difficulty, cognitive competence and affect had medium total affects on achievement and value had no total affect on achievement. In sum, their results indicated that both prior achievement and attitude toward statistics variables impact engineering students' achievement in introductory statistics courses (Figure 2.2.).

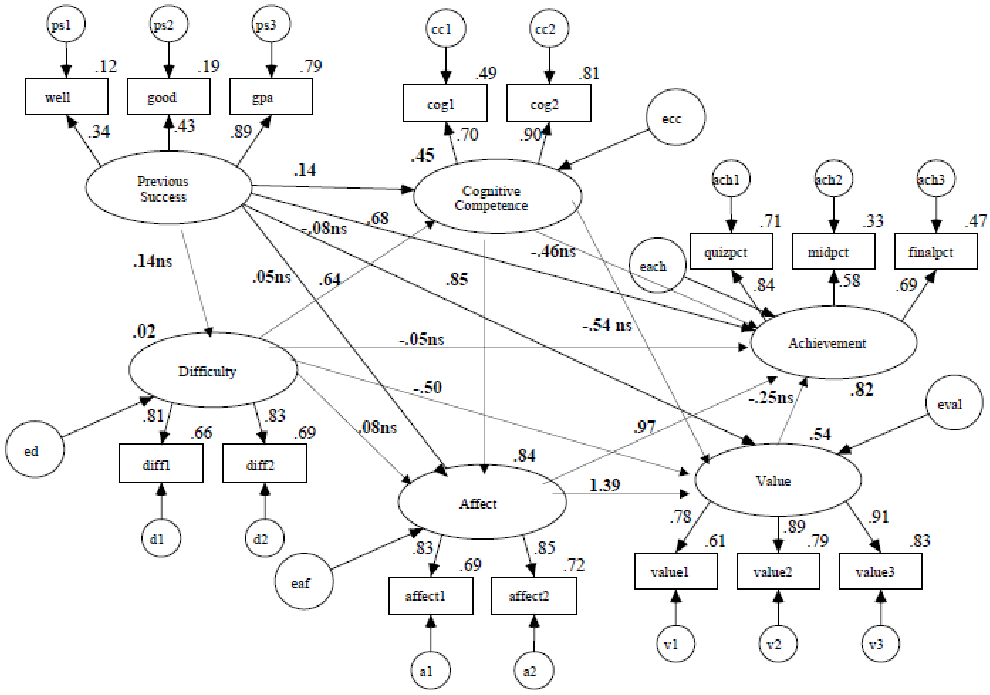


Figure 2.2 Saturated "Statistics Attitudes-Achievement Model" with Standardized Parameters. Note: ns= non-significant, other paths are significant at *p*<.05, *Source:* Sorge and Schau, 2002. Reprinted with authors' permission.

Their study contributed to the current literature for many ways. It included a hypothesized model that is consistent with theoretical framework. The "Statistics Attitudes-Achievement Model" was mainly based on expectancy value theory and several other attitude and learning theories. They used the most current and widely used statistics attitude instrument at the time of the study. Findings of their study were consistent to other studies by demonstrating the complex relationships between attitudes toward statistics and statistics achievement (Bandalos, Finney, & Geske, 2003; Bude´ et al., 2009; Nasser, 2004; Tempelaar et al., 2007). However, the instrument used in their study was the earlier version of Survey of Attitudes toward Statistics© (SATS-28©). Therefore, a need has emerged to modify their “Statistics Attitudes-Achievement Model” by using the current version of Survey of Attitudes toward Statistics© (SATS-36©). For this purpose, their model was extended to “Statistics Attitudes-Outcomes Model” in the current study.

The most visible differences between their “Statistics Attitudes-Achievement Model” and “Statistics Attitudes-Outcomes Model” are that interest and effort constructs are included in “Statistics Attitudes-Outcomes Model”. In addition, statistics achievement variable in “Statistics Attitudes-Achievement Model” was replaced with statistics outcome variable in the current study. Lastly, Sorge and Schau’s (2002) “Statistics Attitudes-Achievement Model” was modified by replacing previous achievement construct to the mathematics achievement in the current study. Because most of the participants of this study did not have any prior experience in statistics but they had prior experience in mathematics.

2.6. Research on Attitudes Toward Statistics in Turkey

A limited number of studies examined students’ attitudes toward statistics in Turkey. These studies mostly included correlational and experimental designs. A review of these studies is presented in this section.

A number of correlational studies were conducted to investigate the correlates of attitudes toward statistics. Aksu and Bikos (2002) examined the role of departmental affiliation, previous statistics experience and gender on explaining students’ attitudes toward statistics. They measured attitudes toward statistics by developing an instrument that consists of three subscales: commitment to the disciple, beliefs about the utility of the discipline and affective/emotional component. They collected data from educational disciplines graduate students (n = 88) and found that departmental affiliation is a statistically significant predictor of the three dimensions of students' attitudes toward statistics, indicating that students from math/science education departments had more positive attitudes toward statistics. More currently, Emmioğlu, Çapa-Aydın, and Çobanoğlu (2010) investigated students' attitudes toward statistics as the predictors of statistics achievement. They used SATS-36© to measure students' attitudes toward statistics. Collecting data from graduate students (n = 54) from education disciplines, they found that students' attitudes toward the difficulty of statistics and the effort students put to learn statistics are statistically significant predictors of statistics achievement. That is, the more students perceived statistics as easy and the more they determined to spend effort in statistics, their statistics achievements were high. Further, Emmioğlu and Çapa-Aydın (2011) conducted a meta-analysis by reviewing the current literature. They investigated the correlations between statistics achievement and four components of attitudes toward statistics (students' affect toward statistics, valuing of statistics, cognitive competence in statistics, and perceptions about the difficulty of statistics). They reported that students' cognitive competence in statistics and affect toward statistics had medium and statistically significant relationship with statistics achievement when students' attitudes toward the value of statistics and difficulty of statistics had small but statistically significant relationship with statistics achievement.

In an experimental study by Doğan (2009), he compared computer based instruction group (n = 35) and control group (n = 35) undergraduate students' attitudes toward statistics and statistics achievement. He developed and administered a one dimensional, 34-item scale to measure students' attitudes. Results indicated that computer based instruction increased both students' statistics achievement and attitudes toward statistics. Another experimental study was conducted by Yılmaz (2006). In her dissertation study, she investigated the effects of real-data and calculator supported activities on 7th

graders' (n = 84) performance and attitudes toward statistics. She divided her sample into three groups: calculator and real-data based (n = 27), real data based (n = 29), and a control group (n = 28). The statistics attitude measure was developed by the researcher that included two subscales: enjoyment and confidence in statistics. In the result of her study, Yılmaz (2006) reported no significant differences among groups in terms of students' attitudes toward statistics and statistics achievement. Similar to Yılmaz (2006), Çalıkoğlu-Bali (2000) investigated students' attitudes toward statistics in her dissertation. She collected data from graduate students of four education faculties (n = 143) and developed an instrument to measure attitudes toward statistics. She concluded that students' perceived competency in statistics was predicted by students' gender, learning styles, enrolled universities, and by attitudes toward statistics variables measured by using statistics in research, impact of statistics on daily life, and importance of statistics.

In sum, research on attitudes toward statistics is a new area in Turkey. In the existing studies conducted in Turkey, researchers developed their own instruments to measure statistics attitudes (Aksu & Bikos, 2002; Çalıkoğlu-Bali, 2000; Doğan, 2009; Yılmaz, 2006). Accordingly, they adopted different perspectives for the components of attitudes toward statistics. Most of these studies focused on different factors influencing students' attitudes toward statistics (Aksu & Bikos, 2002; Çalıkoğlu-Bali, 2000; Doğan, 2009; Yılmaz, 2006). Considering the lack of research in the field, it is evident that there is a need for doing more research on understanding Turkish students' attitudes toward statistics.

2.7. Summary

Attitude is a multidimensional construct that has been studied for many years in education and psychology. These studies mainly focused on the relationship between individuals' attitudes and behaviors. Although attitude concept has been the core issue for many years, attitudes toward statistics has currently gained attention in the field of statistics education.

In the current study, a "Statistics Attitudes-Outcomes Model" is hypothesized to investigate the structural relationships among mathematics achievement, attitudes toward statistics, and statistics outcomes. The theoretical background of the model is based on learning theories, self-efficacy theory, self-determination theory, the theory of planned behavior, and, mainly, expectancy value theory. The hypothesized "Statistics Attitudes-Outcomes Model" is also based on "Statistics Attitudes-Achievement Model", which was developed and tested by Sorge and Schau (2002).

A number of instruments have been developed to measure students' attitudes toward statistics. From these instruments, Survey of Attitudes toward Statistics-36© (SATS-36©) is the most current and widely used instrument. The SATS-36© has been used in various studies, which included samples from different educational levels, majors and nationalities (Barkatsas, Gialamas, & Bechrakis, 2009; Chiesi & Primi, 2009; Coetzee & van der Merwe, 2010; Tempelaar et al., 2007; Verhoeven, 2009). These studies indicated that the SATS-36© has good psychometric properties (Carnell, 2008; Tempelaar et al., 2007; Verhoeven, 2009). For these reasons, the SATS-36© was used in the current study to collect data.

The review of international literature revealed that limited but growing number of studies that focused on statistics attitudes have been conducted. In terms of research designs, these studies can be categorized as correlational, pre-post design, and experimental studies. In addition, structural models were developed to examine the structural relationships among several attitudes toward statistics variables and statistics outcomes. These studies revealed that mathematics achievement and students' attitudes toward statistics are important factors for explaining students' statistics outcomes. Some of these studies suggested that using different methods in statistics instruction would enhance students' positive attitudes toward statistics.

The number of research studies related to attitudes toward statistics is limited in Turkey. In these studies, researchers mostly developed their own instruments to measure statistics attitudes (Aksu & Bikos, 2002; Çalıkoğlu-Bali, 2000; Doğan, 2009; Yılmaz, 2006) and they focused on different research questions related to students' attitudes toward statistics (Aksu & Bikos, 2002; Çalıkoğlu-Bali, 2000; Doğan, 2009; Emmioğlu, Capa-Aydın, & Çobanoğlu (2010; Yılmaz, 2006). As these studies had different conceptualizations of statistics attitudes and emphasized on different research questions, it is highly difficult to compare and contrast these studies.

The review of literature demonstrated that research into students' attitudes toward statistics is in its early stages and the number of studies is very limited. Available research shows that students' attitudes toward statistics, mathematics achievement and students' statistics course outcomes are related; although, the nature of this relationship has not yet fully discovered.

CHAPTER III

METHOD

This chapter includes overall research design, research question, description of variables, data sources, data collection instrument, data collection procedure, data analysis, and limitations of the study.

3.1. Overall Research Design

The design employed in this study is a survey design. A survey design provides quantitative or numeric descriptions of trends, attitudes, or opinions of the participants of the study (Creswell & Miller, 2000). In order to provide these descriptions, a questionnaire is administered to the subjects of the survey design study (Babbie, 2007). In the current study, survey design was adopted and a questionnaire was used in order to gather information on students' attitudes toward statistics, mathematics achievement, and statistics outcomes. Considering the research question of the study, the study also used correlational techniques by examining the relationships of responses to the questions in survey or several other variables (Fraenkel & Wallen, 2003). This study aimed to investigate the structural relationships among students' attitudes toward statistics, mathematics achievement, and statistics outcomes.

The current study was started with an extensive review of literature. Based on the literature, the research question of the study was constructed. Next, Survey of Attitudes toward Statistics-36© (SATS-36©; Schau, et al., 1995; Schau,

2003) consisting of 36 items and six subscales was chosen and adapted to Turkish Turkish language as a data collection instrument.
Depending on the research question of the study, the hypothesized model, “Statistics Attitudes-Outcomes Model”, that proposes the empirical relationships between self-reported mathematics achievement, attitudes toward statistics and statistics outcomes was constructed. Followed by the model construction, target population of the study was selected. The target population was the undergraduate and graduate students enrolled in statistics courses in a university in Turkey.

As the participants of the study were Turkish-speaking students, the instrument was adapted to Turkish context before the collecting the data for the main study. For this purpose, the SATS-36© was translated into Turkish language by back translation method. Next, the Turkish version of the SATS-36© was administered to 347 students at the beginning of the 2009 fall semester to examine its psychometric characteristics. Confirmatory factor analysis was used to test the factorial structure. Reliability estimates were calculated to test the score reliability of the Turkish version of the SATS-36©. After the instrument adaptation procedure, data collection process for the main study was applied. In this step, the Turkish version of the SATS-36© consisting of six subscales (cognitive competence, affect, value, difficulty, effort, and interest) and additional questions (i.e. self-reported mathematics achievement) was administered to the participants (n = 247) at the end of the 2009-2010 fall and spring semesters. After the data collection, the negatively worded items were reversed and data were screened in terms of necessary assumptions required for the subsequent data analyses.

Finally, the hypothesized model was tested by Structural Equation Modeling (SEM) technique using Mplus software student version 5.21 (Muthen & Muthen, 2007). The model was evaluated by several model fit indexes such as

Chi-Square, CFI, RMSEA, and SRMR along with the parameter estimates. The steps of the research design adopted in the current study are presented in Figure 3.1.

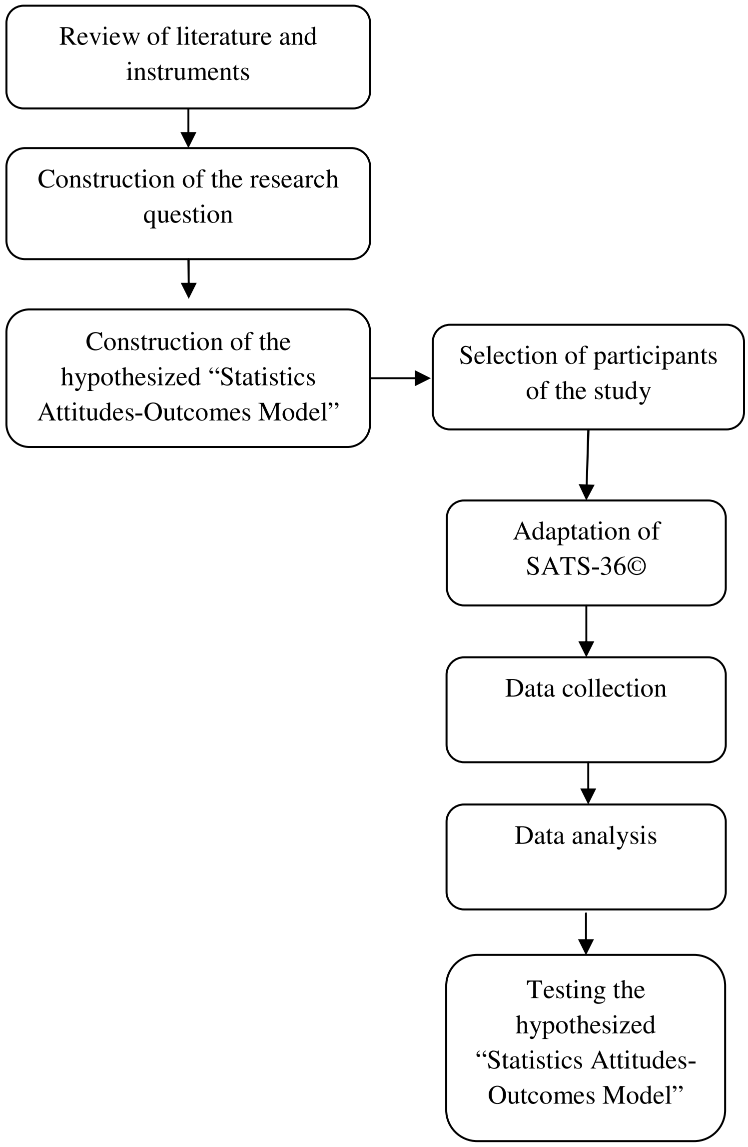


Figure 3.1 Steps of the Current Research Design

3.2. Research Question

The main research question addressed in this study was the following: What is the nature of the relationship among self-reported math achievement (self-reported past mathematics achievement and self-reported overall mathematics achievement), attitudes toward statistics (cognitive competence, affect, value, difficulty, effort, and interest) and statistics outcomes (total grade earned at the end of taking the statistics course, willingness to use statistics in the remainder of the degree program, and willingness to use statistics when employed)?

In order to investigate the research question of the study, the "Statistics Attitudes-Outcomes Model" was hypothesized and tested. The hypothesized "Statistics Attitudes-Outcomes Model" is presented in Figure 3.2.

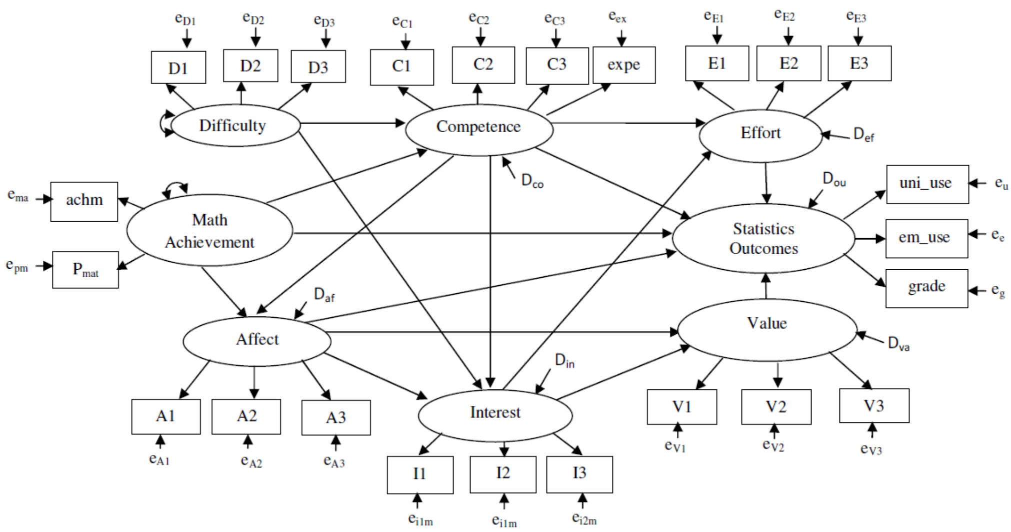


Figure 3.2 The Hypothesized "Statistics Attitudes-Outcomes Model"

Note: The direction of the arrows shows the direction of the hypothesized relationships/direct effects among the variables, Math achievement: Self-reported Math Achievement, A1-A3: Affect item parcels, Competence: Cognitive Competence, C1-C3: Cognitive Competence item parcels, V1-V3: Value item parcels, D1-D3: Difficulty item parcels, E1-E3: Effort item parcels; I1-I3: Interest item parcels, expe= Expectancy of Success, p_{mat}=Self-reported Previous Math Achievement, achm=Self-reported Overall math achievement, em_use= willingness to use statistics when employed, uni_use= willingness to use statistics in the remainder of the degree program

3.3. Description of Variables

Difficulty is the exogenous variable of the study because it is not proposed to be predicted by other variables of the hypothesized "Statistics Attitudes-Outcomes Model" (Weston & Gore, 2006). Difficulty was measured by seven-item "Difficulty" component of the SATS-36©, which has a seven-point response scale (1 = strongly disagree, 4 = neither disagree nor agree, 7 = strongly agree). It is important to note here that difficulty subscale measured students' perceptions about the difficulty of statistics for any individual, instead of their perceptions about the difficulty of statistics for themselves. In the current study, higher scores in difficulty subscale indicated "lack of difficulty", which means that students with higher difficulty scores are assumed to perceive statistics as an "easy" subject.

Mathematics achievement is also the exogenous variable of the study as it is not proposed to be predicted by other variables of the hypothesized "Statistics Attitudes-Outcomes Model" (Weston & Gore, 2006). Mathematics achievement involved two components: self-reported past mathematics achievement and self-reported overall mathematics achievement. Self-reported past mathematics achievement was measured by the item: How well did you do in mathematics courses you have taken in the past? Students were asked to rate their answer on a seven point response scale (1= very poorly, 7= very well). Self-reported overall mathematics achievement was measured by the item: How good at mathematics are you? Students were asked to rate their answer on a seven point response scale (1 = very poor, 7 = very good). High scores in mathematics achievement component indicated that students have high self-perceptions of their past and overall mathematics achievement.

Cognitive competence is an endogenous variable of the current study as it is proposed to be predicted by difficulty and mathematics achievement variables.

Cognitive competence was measured by the six-item cognitive competence component of the SATS-36©, which has a seven-point response scale (1 = strongly disagree, 4 = neither disagree nor agree, 7 = strongly agree). In addition, cognitive competence was measured by expectancy of success variable, which was measured by the item: "What grade do you expect to receive in this course?" Students were asked to rate their expected grade on a nine point scale (1 = less than 49, 2 = 50-59, 3 = 60-64, 4 = 65-69, 5 = 70-74 6 = 75-79, 7 = 80-84, 8 = 85-89, 9 = 90-100). Higher cognitive competence scores indicated students' positive perceptions of their intellectual knowledge and skills when applied to statistics.

Interest is an endogenous variable of the current study since it is proposed to be predicted by cognitive competence, difficulty, and affect variables. Interest was measured by four-item interest subscale of the SATS-36©, which has a seven-point response scale (1 = strongly disagree, 4 = neither disagree nor agree, 7 = strongly agree). In this study, higher scores in interest subscale indicated students' higher levels of individual interest in statistics.

Affect is an endogenous variable of the current study since it is proposed to be predicted by mathematics achievement and cognitive competence. Affect was measured by six-item affect component of the SATS-36©, which has a seven-point response scale (1 = strongly disagree, 4 = neither disagree nor agree, 7 = strongly agree). In the current study, students' higher scores of affect subscale indicated their positive feelings concerning statistics.

Effort is an endogenous variable of the current study since it is proposed to be predicted by cognitive competence and interest variables. Effort was measured by four-item effort component of the SATS-36©, which has a seven-point response scale (1 = strongly disagree, 4 = neither disagree nor agree, 7 =

strongly agree). Higher scores in effort subscale indicated that students devoted high effort in statistics.

Value is an endogenous variable of the current study since it is proposed to be predicted by affect and interest variables. Value was measured by nine-item value component of the SATS-36©, which has a seven-point response scale (1 = strongly disagree, 4 = neither disagree nor agree, 7 = strongly agree). Higher scores in value subscale indicated positive attitudes about the usefulness, relevance, and worth of statistics in personal and professional life.

Statistics outcomes is the dependent or outcome variable of the study; because, statistics outcomes variable is proposed to be predicted by other variables of the model but not proposed to predict any variable presented in the model. Statistics outcomes variable composed of three components: grade, willingness to use statistics in the remainder of the degree program, and willingness to use statistics when employed. Grade was measured by students' total grade earned at the end of taking a statistics course. The information was obtained from Student Affairs' Information System of the university after Student Affairs' Registration Office announced students' letter grades. Willingness to use statistics in the remainder of the degree program was measured by the item: "As you complete the remainder of your degree program, how much will you use statistics?" Willingness to use statistics when employed was measured by the item: "In the field in which you hope to be employed when you finish school, how much will you use statistics?" For both questions, students were asked to rate their willingness on a seven-point response scale (1 = not at all, 7 = great deal).

3.4. Data Sources

The participants of the study were 247 undergraduate and graduate students enrolled in statistics courses in a university in Turkey. Participants were neither having an undergraduate study nor seeking a graduate degree in the field of statistics. Accordingly, the target population of the study was all non-statistician students taking statistics courses at the 2009-2010 academic year in a 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. For this purpose, firstly, Student Affairs' Information System of the university was used to gather information about the service statistics courses offered to non-statistician students. Secondly, these courses were listed. Thirdly, professors of the courses were asked their approval for their students to participate in this study. From 18 professors, 13 of them agreed that their students could participate. These students yielded the accessible population. Consequently, data were collected from the accessible population members who volunteered to participate in the study. Four of the students did not volunteer to participate in the study. Finally, the study was carried out with 247 undergraduate and graduate students enrolled in statistics courses. As stated by Kline (2005), in order to test a structural equation model, the sample size should be at least 200. Considering Kline's (2005) criteria, it is plausible to state that the number of participants involved in the current study was appropriate for the data analysis used in the current study.

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 engineering (26.3%), followed by education (23.1%), economics (13.8%), psychology (12.6%), sociology (8.5%), applied mathematics (4.9%), and business administration (3.2%).

Table 3.1

Frequency and Percentages of Students' Major (n = 247)

	f	%
Education	57	23.1
Psychology	31	12.6
Sociology	21	8.5
Economics	34	13.8
Business Administration	8	3.2
Applied Mathematics	12	4.9
Engineering	65	26.3
Missing	19	7.7

The frequency distributions of participants' degrees and grade levels were presented in Table 3.2. In terms of the degrees students were seeking; 63.2% of them were undergraduate, and 32.4% of them were graduate students. From all of the participants of the study, 23.1% were M.Sc. and 9.3% were Ph.D. students. In terms of the grade level, 36% of the participants were second year, 21.1% of them were third year, and 6.1% of them were 4^{th} year undergraduate students.

Table 3.2

Frequency Distribution of Students' Degree and Grade Level (n=247)

	f	%
2^{nd} year undergraduate	89	36.0
3^{rd} year undergraduate	52	21.1
4^{th} year undergraduate	15	6.1
Total undergraduate	156	63.2
M.Sc.	57	23.1
Ph.D.	23	9.3
Total graduate	80	32.4
Missing	11	4.4

3.5. Data Collection Instruments

The Turkish version of the Survey of Attitudes toward Statistics-36© (SATS-36©) was used to collect data. The SATS-36© was utilized in this dissertation 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 (Chiesi & Primi, 2009; 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 (Barkatsas, Gialamas, & Bechrakis, 2009; Chiesi & Primi, 2009; Coetzee & van der Merwe, 2010; Tempelaar et al., 2007; Verhoeven, 2009).

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".

The SATS-36© has pre and post versions to measure students' attitudes toward statistics at the beginning and at the end of a statistics course. The only difference between pre and post versions of the survey is the grammatical verb tense used. For example, the item 'I plan to study hard for every statistics test' in pre version corresponds to the item 'I tried to study hard for every statistics test' in post version of the SATS-36©. Post SATS-36© items with their corresponding components are presented in Table 3.3.

Table 3.3

Post SATS-36© Items

SATS-36© Components	Items
Affect	3. I like statistics. 4.*. I feel insecure when I have to do statistics problems. 15.* I get frustrated going over statistics tests in class 18.* I am under stress during statistics courses. 19. I enjoy taking statistics courses. 28.* I am scared by statistics.
Cognitive Competence	5.* I have trouble understanding statistics because of how I think. 11.* I have no idea of what's going on in this statistics course 26.* I make a lot of math errors in statistics. 31. I can learn statistics. 32. I understand statistics equations. 35.* I find it difficult to understand statistical concepts.
Value	7.* Statistics is worthless. 9. Statistics should be a required part of my professional training. 10. Statistical skills will make me more employable. 13.* Statistics is not useful to the typical professional. 16.* Statistical thinking is not applicable in my life outside my job. 17. I use statistics in my everyday life. 21.* Statistical conclusions are rarely presented in everyday life. 25.* I will have no application for statistics in my profession. 33.* Statistics is irrelevant in my life
Difficulty	6. Statistics formulas are easy to understand 8.* Statistics is a complicated subject. 22. Statistics is a subject quickly learned by most people. 24.* Learning statistics requires a great deal of discipline. 30.* Statistics involves massive computations. 34.* Statistics is highly technical. 36.* Most people have to learn a new way of thinking to do statistics.
Interest	12. I am interested in being able to communicate statistical information to others. 20. I am interested in using statistics 23. I am interested in understanding statistical information. 29. I am interested in learning statistics.
Effort	1. I tried to complete all of my statistics assignments. 2. I worked hard in my statistics course 14. I tried to study hard for every statistics test. 27. I tried to attend every statistics class session.

*reversed items

The SATS-36© has been used in many studies that included participants with varying ethnicities and nationalities including Italian, Dutch, Israeli, and South African. These studies demonstrated that the survey exhibited good psychometric properties when administered across different cultural contexts

(Chiesi & Primi, 2009; Coetzee & van der Merwe, 2010; Hilton et al., 2004; Tempelaar et al., 2007; Verhoeven, 2009). Tempelaar et al. (2007) and Verhoeven (2009) tested the fit of their data to the six-factor model by utilizing Confirmatory Factor Analysis. Their results indicated that their data from Netherlands sample fit the hypothesized six factor model with CFI values exceeding .95 and RMSEA values about .06 indicating good fit (Hu & Bentler, 1999; Kline, 2005). As for the internal consistency of the scores, Cronbach alpha coefficients were calculated. The coefficients were reported as the following: affect: .80-.82, cognitive competence: .77-.82, value: .78-.82, difficulty: .68-.75, interest: .80-.84, and effort: .76-.80 (Tempelaar et al., 2007; Verhoeven, 2009). The data collection scheme of the variables along with the corresponding components, and sample items are presented in Table 3.4.

Table 3.4

Description of Variables

Variables	*Components*	*Sample Items*	*Coding scheme*
Mathematics achievement	Self reported past mathematics achievement	How well did you do in mathematics courses you have taken in the past?	(1) very poorly (7) very well
	Self reported overall math achievement	How good at mathematics are you?	(1) very poor (7) very good
Attitudes toward Statistics	Cognitive Competence	What grade do you expect to receive in this course? (Expectancy of Success)	(9) 90-100 (8) 85-89 (7) 80-84 (6) 75-79 (5) 70-74 (4) 65-69 (3) 60-64 (2) 50-59 (1) less than 49
		I can learn statistics.	(1) strongly disagree (4) neither disagree nor agree (7) strongly agree
	Affect	I like statistics.	
	Value	Statistical skills will make me more employable.	
	Difficulty	Statistics formulas are easy to understand	
	Effort	I worked hard in my statistics course	
	Interest	I am interested in using statistics	

Table 3.4

Description of Variables (*cont.*)

Variables	*Components*	*Sample Items*	*Coding scheme*
Statistics Outcomes	Grade	Students' total grade earned after taking statistics courses were obtained from Student Affairs' Registration Office of the university	(7) 90-100 (6) 85-89 (5) 80-84 (4) 75-79 (3) 65-69 (2) 60-64 (1) 50-59
	Willingness to use statistics in the remainder of degree program	As you complete the remainder of your degree program, how much will you use statistics?	(1) not at all (7) great deal
	Willingness to use statistics when employed	In the field in which you hope to be employed when you finish school, how much will you use statistics?	

3.6. Adaptation of the Survey of Attitudes Toward Statistics© into Turkish

In order to adapt the SATS-36© into Turkish language, firstly, instrument was translated into Turkish language by using back translation method; secondly, data were collected using Turkish version of the SATS-36©; and thirdly, data were analyzed in order to investigate the score validity and reliability.

Back translation method was used to obtain the Turkish version of the SATS-36©. The survey was translated from English to Turkish by five experts. These experts were two English language teachers, one assistant professor in Measurement and Evaluation, one Ph.D. candidate in Guidance and Psychological Counseling, and one Ph.D. candidate in Curriculum and Instruction. Based on the consistencies of the five translated forms, one version of the Turkish SATS-36© was selected.

The Turkish SATS-36© was back translated by three other experts. These experts were two Ph.D. candidates in Curriculum and Instruction and an English teacher. Lastly, the original SATS-36© and the back translated form was examined with regard to the consistencies. A strong consistency (about 90%) was found between two forms, indicating that the Turkish version of the SATS-36© is a consistent version of the original SATS-36©.

In the current study, pre SATS-36© was translated to Turkish language; however, post version of SATS-36© was used to collect data. In Turkish language, derivational affixes are added to word in order to change the verb tense from present tense to past tense. Therefore, the Turkish version of post-SATS-36© was obtained from the Turkish version of the pre-SATS-36© by changing the affixes according to the verb tense.

In the pilot study, the Turkish version of the SATS-36© was administered at the beginning of the 2009 fall semester of which participants (n = 347, 59.4% female and 36% male) enrolled in thirteen statistics course sections. The students were majoring at various areas including: education (n = 69), psychology (n = 44), economics (n = 108), business administration (n = 31), engineering (n = 70), and applied mathematics (n = 23). However, two students did not report their majors. The mean age was M = 23.16 years (SD = 2.29). Of all the students, 231 (66.57%) were undergraduate and 108 (31.1%) were graduate students.

A confirmatory factor analysis was performed to assess the six-factor structure of the Turkish version of SATS-36©. These factors were affect, cognitive competence, difficulty, effort, interest, and value. Mplus statistical modeling software 5.21, student version was used to run confirmatory factor analysis. SPSS 15 software was used to calculate Cronbach alpha values to examine the internal consistency of the survey subscales.

Prior to the confirmatory factor analysis, an item parceling procedure was adopted. Instead of using individual items, item parceling was used in order to obtain more continuous and normally distributed data. Item parceling is also used to reduce the number of model parameters to get more stable parameter estimates (Bandalos, 2008; Tempelaar et al., 2007); because, the number of indicators are reduced when item parcels are used instead of individual items.

Item parceling is a method that refers averaging item scores from two or more items from the same scale to use in place of the item scores in a Structural Equation Modeling (SEM) analysis (Bandalos, 2008, p.212). In the current study, Tempelaar et al.'s (2007) item parceling scheme was adopted. That is, same items were assigned to specific item parcels as they did in their study (personal communication, November 16, 2009).

All of the items in each subscale (affect, cognitive competence, difficulty, effort, interest, and value) were divided into three item parcels. For example, items of affect components were gathered into three item parcels. First item parcel of the affect construct was generated by calculating the mean of the item 15 (I get frustrated going over statistics tests in class) and item 28 (I am scared by statistics). The second item parcel of the affect was generated by calculating the mean of the item 3 (I like statistics) and 4 (I feel insecure when I have to do statistics problems). The third and the last item parcel of the affect was generated by calculating the mean of the item 18 (I am under stress during statistics courses) and item 19 (I enjoy taking statistics courses).

In the pilot study, in order to provide information in terms of the distribution of item parcels, Skewness and Kurtosis values were inspected. Skewness is defined as a measure of symmetry of a distribution, whereas Kurtosis is defined as a measure of the peakedness or flatness of a distribution (Hair, Anderson, Tatham, & Black, 1998). The distribution is perfectly normal when Skewness and Kurtosis values are zero (Tabachnick & Fidell, 2007). Variables with absolute values of the Skewness index greater than 3 are described as extremely skewed, whereas the absolute values of the Kurtosis index greater than 10 suggests problem (Kline, 2005). In the pilot study, Skewness and Kurtosis values of the item parcels ranged from -.03 to 3.87. That is, item parceling procedure used in the current study resulted with approximately normal item parcels. The Skewness and Kurtosis values for the corresponding item parcels are presented in Table 3.5

Table 3.5

Item Parcels and Skewness and Kurtosis Values for the Pilot Study (n=347)

Item Parcels	*Skewness*	*Kurtosis*
A1	-.39	-.51
A2	-.61	.19
A3	-.41	-.47
C1	-.72	.30
C2	-.70	.09
C3	-.65	.18
V 1	-.67	.39
V 2	-.71	.54
V3	-.83	.55
D1	-.03	-.19
D2	.19	-.46
D3	-.06	-.20
E1	-.83	.60
E2	-1.01	1.09
E3	-1.67	3.87
I1	-.28	-.63
I2	-.31	-.96
I3	-.72	-.21

Running the confirmatory factor analysis, each item parcel 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 of 286.95 with 120 degrees of freedom, $p<.05$. In addition to the model chi-square, Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) fit indices were inspected. Values of these indexes were: CFI = .95, SRMR = .07 and RMSEA = .06 with a confidence interval of .05 to .07. 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, 2005). After inspecting the overall fit of the model to the data, the standardized parameter estimates are examined (Figure 3.3).

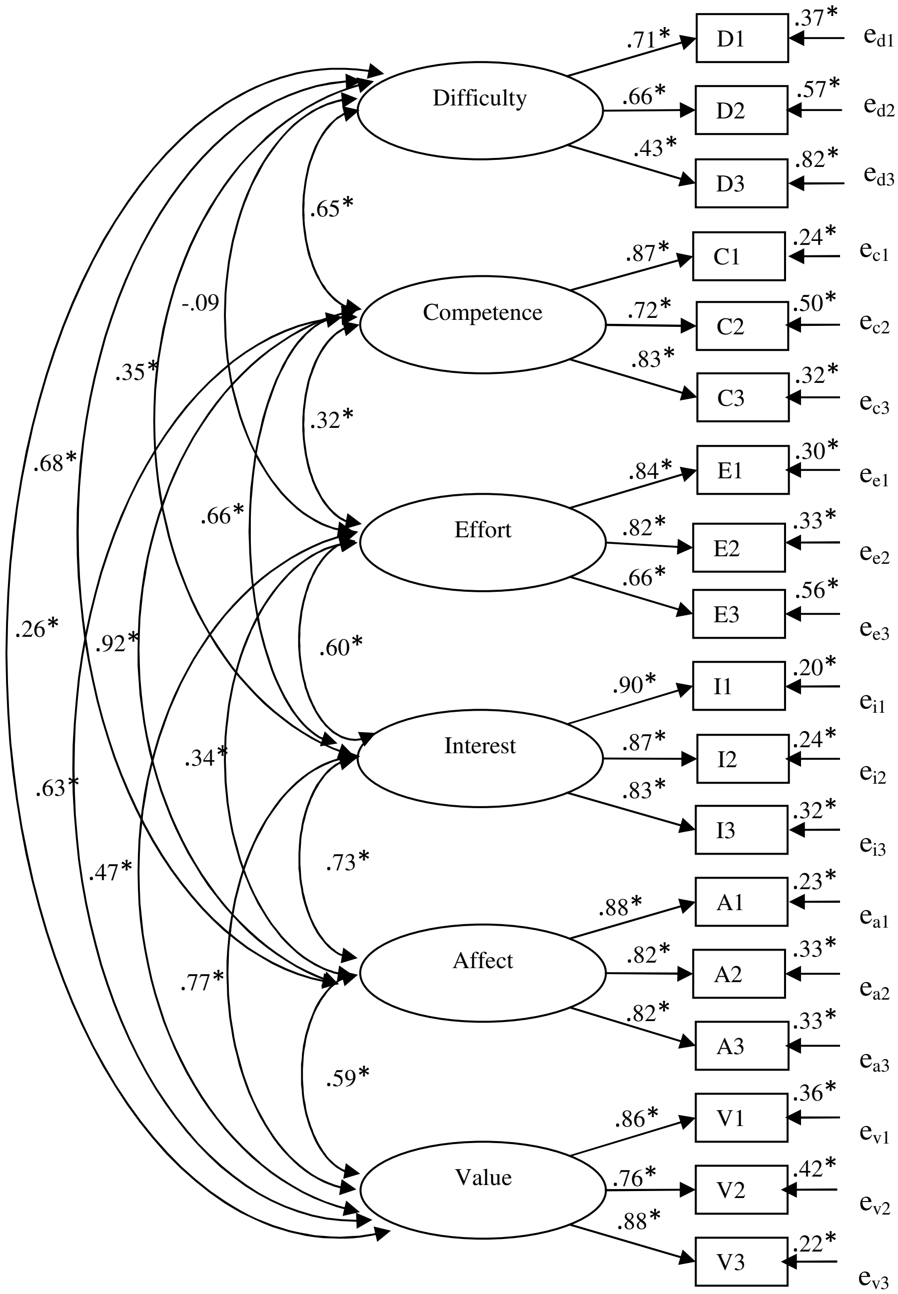


Figure 3.3 Confirmatory Factor Analysis of the Turkish Version of SATS-36©

Note. *p<.05, A1-A3: Affect item parcels, Competence: Cognitive Competence, C1-C3: Cognitive Competence item parcels, V1-V3: Value item parcels, D1-D3: Difficulty item parcels, E1-E3: Effort item parcels; I1-I3: Interest item parcels

As seen in Figure 3.3, the results of the standardized parameters estimates (factor loadings) suggested that item parcels measured the corresponding factors of the Turkish version of the SATS-36© well. That is, the standardized estimates of factor loadings ranged from .43 to .90, all statistically significant. This finding was consistent with earlier studies (Sorge & Schau, 2002; 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 3.3). The estimated correlation between affect and cognitive competence was very strong ($r = .92$) and statistically significant; however, this finding was expected and desired as the same pattern was found in previous studies (Dauphinee et al., 1997; Schau et al., 1995; Sorge & Schau, 2002; Tempelaar et al., 2007). Moreover, these constructs are accepted as theoretically and empirically distinct although they are highly correlated (Dauphinee et. al., 1997; 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 (See 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 it 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 = .85, cognitive competence = .82, value = .85, difficulty = .69, interest = .90, effort = .81. Results indicated that difficulty subscale produced adequately reliable scores while the other subscales produced score reliabilities that ranged from "good" to "excellent" (Kline, 2005). These values are consistent with previous research, indicating that reliable scores were obtained when the Turkish 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; Verhoeven, 2009).

3.7. Data Collection Procedures

Main study was conducted to test the hypothesized "Statistics Attitudes-Outcomes Model". The Turkish version of the post-SATS-36© was used to collect data after permissions were obtained from Research Center for Applied Ethics' committee. Data collection procedure took place at the end of 2009 fall (n = 180) and 2010 spring (n = 67) semesters. As the number of participants obtained in 2009 fall semester (n = 180) was not big enough to conduct SEM analyses (Kline, 2005), the data were collected not only in 2009 fall semester but also in 2010 spring semester. Researcher administered the post SATS-36© to the students during classroom hours. Students were informed that their participation would be voluntary, anonymous, and confidential. The administration of the instrument took about 15 to 20 minutes.

3.8. Data Analysis

Structural Equation Modeling (SEM) was used in order to test the hypothesized model of the study. In this study, the alpha level for all significance tests was set at the .05 level, which is a convention criterion for a minimum basis for rejecting the null hypothesis in most areas of behavioral science (Cohen, 1988). Prior to the data analysis, firstly, the data were screened for several characteristics (missing data, influential outliers, normality, linearity, homoscedasticity, and multicollinearity) by using SPSS 15 program. Secondly, descriptive statistics were provided in order to describe participants' characteristics, frequencies, percentages, means, standard deviations, and bivariate correlations were investigated. SPSS 15 software was used to run descriptive statistics. Thirdly, item-parceling procedure was applied prior to the SEM analysis. Item parcels reduce the number of indicators, so that researchers can use more realistic models that better capture complex theories of human behavior (Nasser & Wisenbaker, 2003). Item parceling is used in empirical studies for several other reasons: (1) to obtain more continuous and normally distributed data, (2) to reduce the number of model parameters, and (3) to get more stable parameter estimates (Bandalos, 2008; Tempelaar et al., 2007).

In the current study, item parceling scheme for the six subscales of the SATS-36© was taken from Tempelaar et al.'s study which was conducted in 2007 (personal communication, November 16, 2009). However, in this study, a minor addition was applied to their parceling scheme. Depending on Eccles' Model (Eccles & Wigfield, 2002), expectancy of success was added to the latent variable of cognitive competence as another item parcel. Consequently, except that cognitive competence possessed four item parcels, each of the SATS-36© subscales had three item parcels. Math achievement had two item parcels: self reported past mathematics achievement and self reported overall mathematics achievement. Statistics outcomes variable had three item parcels. These were grade, willingness to use statistics in the remainder of the degree program, and willingness to use statistics when employed. As stated earlier, one of reasons for using an item parceling procedure is to get normally distributed data.

As seen in Table 3.6, item parcels in the main study were close to normal since they did not deviate much from the Skewness and Kurtosis value of zero (Tabachnick & Fidell, 2007). That is, item parceling procedure utilized in this study was useful for forming normally distributed data; because, Skewness values of the items parcels ranged from .06 to -1.10 and Kurtosis values ranged from .01 to 1.27.

Table 3.6

Means, Standard Deviations, Skewness and Kurtosis Values of Indicators (n=247)

	M	*SD*	*Skew.*	*Kurt.*
I1 (Interest item parcel 1)	4.12	1.59	-.09	-.95
I2 (Interest item parcel 2)	4.25	1.83	-.23	-.99
I3 (Interest item parcel 3)	4.74	1.73	-.56	-.58
E1 (Effort item parcel 1)	4.85	1.54	-.51	-.35
E2 (Effort item parcel 2)	4.74	1.67	-.51	-.59
E3 (Effort item parcel 3)	5.71	1.27	-1.01	.75
V1 (Value item parcel 1)	5.09	1.05	-.50	.62
V2 (Value item parcel 2)	5.08	1.21	-.63	.31
V3 (Value item parcel 3)	4.89	1.29	-.55	.02
C1 (Cognitive Competence item parcel 1)	5.26	1.23	-.83	.65
C2 (Cognitive Competence item parcel 2)	5.29	1.27	-.79	.76
C3 (Cognitive Competence item parcel 3)	5.18	1.27	-.65	.19
Expe(Cognitive Competence item parcel 4)	6.00	2.20	-.54	-.60
D1 (Difficulty item parcel 1)	3.44	1.06	.21	.14
D2(Difficulty item parcel 2)	3.33	1.18	.13	-.54
D3(Difficulty item parcel 3)	3.79	1.18	.06	-.42
A1 (Affect item parcel 1)	4.70	1.59	-.49	-.59
A2 (Affect item parcel 2)	4.46	1.49	-.43	-.35
A3 (Affect item parcel 3)	4.62	1.57	-.59	-.38
Pmat (Math achievement item parcel 1)	5.82	1.24	-1.10	1.27
Achmat (Math achievement item parcel 2)	5.56	1.06	-.48	.01
Emuse (Statistics Outcomes item parcel 1)	4.61	1.56	-.42	-.38
Uniuse (Statistics outcomes item parcel 2)	4.70	1.63	-.39	-.52
Grade (Statistics Outcomes item parcel 3)	4.86	1.97	-.63	-.76

Note: Expe= Expectancy of Success, Pmat=Self-reported Previous Math Achievement, Achmat=Self-reported Overall math achievement, Emuse= willingness to use statistics when employed, Uniuse= willingness to use statistics in the remainder of the degree program

After using the item parceling procedure, as last step of data analysis, structural equation modeling analyses were utilized. The hypothesized "Statistics Attitudes-Outcomes Model" was tested by using Mplus statistical modeling software (Muthen & Muthen, 2007).

Structural Equation Modeling (SEM) refers to a family of related procedures for testing carefully delineated multivariate models based on hypotheses about how observed (i.e., statistics grade) and unobserved variables (i.e., statistics outcomes) are interrelated (Hoyle, 1995). Researchers are able to specify complex relationships based on previous research or theory and they can test those relationships whether they are reflected in the data by using SEM (Weston & Gore, 2006). SEM is a popular statistical tool for researchers in psychology, education, and the social sciences generally (Fan, Thompson, & Wang, 1999). One advantage of SEM is that it allows researchers to think in terms of models, so that many applications of SEM are a blend of exploratory and confirmatory analyses (Kline, 2005). However, the results of the SEM should be interpreted carefully. Despite the fact that researchers hypothesize causal relationships in SEM, causality cannot be determined by the results of SEM analyses, unless researchers analyze longitudinal or experimental data (Weston & Gore, 2006). In order to understand SEM models and SEM results, one should understand the SEM terminology. For this reason, definitions and explanations of the most commonly used concepts are presented below.

Unobserved variables/Latent variables/factors are the variables that cannot be observed directly (Byrne, 1998). In this study, latent variables are difficulty, math achievement, cognitive competence, affect, effort, interest, value, and statistics outcomes.

Observed variables/Indicators/Manifest variables are the variables that are measured to serve as indicators of the underlying construct that they are presumed to represent (Byrne, 1998). In this study, indicators are the item parcels.

Exogenous latent variables are the variables that their causes are unknown and are not represented in the model (Kline, 2005). They are synonymous with independent variables; they cause fluctuations in the values of other latent variables in the model (Byrne, 1998). In this study, the exogenous latent variables are math achievement and difficulty.

Endogenous latent variables are the variables that their presumed causes are explicitly represented in the model (Kline, 2005). In this study, the endogenous variables are cognitive competence, affect, effort, interest, value, and statistics outcomes.

Outcome/dependent variable(s) are the variables that are assumed to be predicted by other variable(s) in the model but not assumed to predict any variable presented in the model.

Disturbances (D) represent all causes of an endogenous variable that are omitted from the structural model (Kline, 2005). Disturbances are analogous to a residual in a prediction equation. For example, in this study, the disturbance of affect refers to the variance of affect construct that are not explained by mathematics achievement and cognitive competence variables.

Measurement error (e) represents error in indicator variable that is not accounted for by latent variable (Weston & Gore, 2006). For example, in the current study, measurement error of expectancy of success indicator refers to variance that is not explained by cognitive competence variable.

Measurement Model is a model that focuses solely on the link between unobserved (latent variables) and corresponding observed variables (Byrne, 1998). The measurement model defines the relations between observed (expectancy of success) and unobserved (latent/construct; for example, cognitive competence) variables.

Structural Model is a model that depicts the links among the unobserved variables themselves (Byrne, 1998).

Structural Regression Model includes a measurement model that represents observed variables as indicators of underlying factors and a structural model that represents the patterns of complex relationships between latent factors.

Direct effects represent a hypothesized direct effect of one variable on another. The arrowhead points to the presumed effect and the line originates from a presumed cause (Kline, 2005). Direct effects are calculated by standardized parameter estimates. Researchers often interpret these estimates as regression coefficients for effects on endogenous variables from other variables that are presumed to directly cause them (Kline, 2005). However, causality should not be determined in a study when data are not analyzed longitudinally or experimentally (Weston & Gore, 2006). In the current study, an example to a direct effect might be the one from difficulty to the cognitive competence.

Indirect effects involve one or more intervening variables presumed to "transmit" some of the causal effects of prior variables onto subsequent variables (Kline, 2005). In the current study, an example to an indirect effect might be the one from difficulty to effort through cognitive competence.

Path coefficients/path weights are interpreted for structural regression models as regression coefficients for effects on endogenous variables from other variables presumed to directly cause them. They control for correlations among multiple presumed causes of the same variable (Kline, 2005).

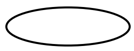
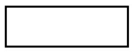
Factor loadings are interpreted for structural regression models as regression coefficients for effects of factors on indicators, just as they are for CFA models (Kline, 2005).

Model estimation procedure's primary focus is to yield parameter values such that discrepancy (residual) between sample covariance matrix and the population covariance matrix implied by the model are minimal (Byrne, 1998). In this study, maximum likelihood parameter estimates with standard errors and a chi-square test statistics that are robust to non-normality (MLR) was used as an estimation method (Muthen & Muthen, 2007). MLR results in the same parameter estimates as maximum likelihood estimation (ML); however, the standard errors and chi-square tests are computed differently. MLR is assumed to be robust against moderate violations of unmodeled heterogeneity as well as non-normality (Hox, Maas, & Brinkhuis, 2010).

In order to understand the visual representation of an SEM model, one should understand the most commonly used symbols appeared in the model. For this reason, the symbols that are used in an SEM model are presented in Table 3.7.

Table 3.7

Common Concepts and Symbols in SEM Models

Concept	*Symbol in figure*
Latent variable, construct, unobserved variable	
Indicator, observed variable	
Measurement error	e
Disturbance	D
Parameter, path coefficient, path loading, direct effect	→
Variance of an exogenous variable	

In the current study, the hypothesized model of the study is a structural regression model that consists of both a measurement and a structural portion, which represents links among the latent variables. The model examined the complex relationships between math achievement (self-reported past mathematics achievement and self-reported overall mathematics achievement), attitudes toward statistics (cognitive competence, affect, value, difficulty, effort, interest), and statistics outcomes (total grade earned at the end of taking the statistics course, willingness to use statistics in the remainder of the degree program, and willingness to use statistics when employed). The relationships proposed in the hypothesized "Statistics Attitudes-Outcomes Model" are presented in Figure 3.4.

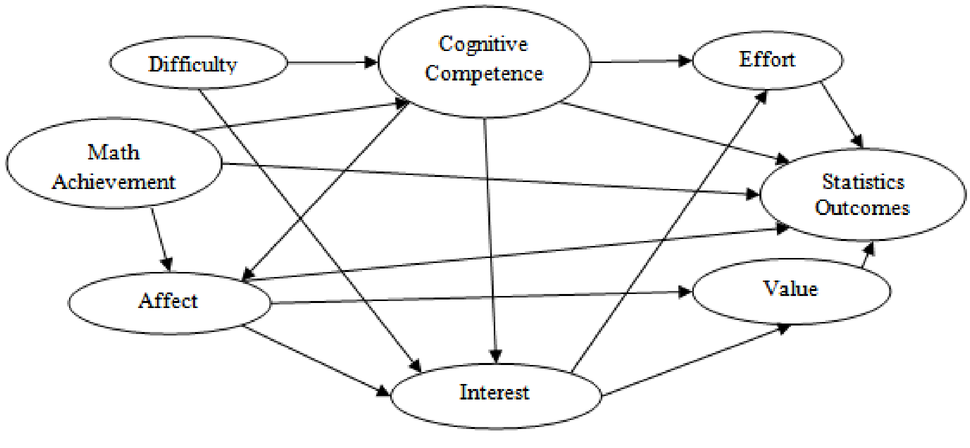


Figure 3.4 The Hypothesized Relationships Proposed in "Statistics Attitudes-Outcomes Model" Note: The direction of the arrows shows the direction of the hypothesized relationships/direct effects among the variables.

In order to evaluate the fit of the hypothesized "Statistics Attitudes-Outcomes Model" to the data, several model fit indices were used as suggested by MacCallum et al. (1996). These were model chi square (χ^2), normed chi square (NC), comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR).

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 differences 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). There are some problems with relying only on model χ^2 as a fit statistics. 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, 2005).

Ratio of Chi-Square to Degrees of Freedom (χ^2/df) was used to reduce the sensitivity of χ^2 to sample size. The value of the χ^2 is divided by the degrees of freedom, which generally results in a lower value called *normed chi square (NC).* Values of the NC of 2.0, 3.0 or even as high as 5.0 have been recommended as indicating reasonable fit and that the NC does not completely correct for the influence of sample size (Bollen, 1989).

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, Hau, & Wen, 2004); however the other group suggests that the widely used criteria of .90 should be increased to .95 (Hu & Bentler, 1999).

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 the best fit and higher values indicate worse fit. RMSEA $\leq$ .05 indicates close approximate fit, values between .08 and .10 indicates mediocre fit, and RMSEA $\geq$ .10 suggests poor fit (MacCallum, Browne, & Sugawara, 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 & Bentler, 1999), whereas values smaller than .10 are generally considered favorable (Kline, 2005).

3.9. Limitations of the Study

The limitations of the current study are discussed below with regard to the internal and external validity threats.

3.9.1. Internal Validity Threats

Internal validity threat is the existence of alternative explanations to the research results. As stated by Gravetter and Forzano (2011), for a research study to have internal validity there must be only one explanation for the research results.

As stated by Fraenkel and Wallen (2003), the particular locations in which data are collected may create alternative explanations for results. In the current study, the data were collected from various statistics course sections from different classroom locations, which might be a threat to internal validity. In addition, the data were collected at the end of both fall and spring semesters; because, the requirement of at least 200 participants to run the SEM analysis (Kline, 2005) could not be reached by collecting data in one semester. However, as the data were collected during regular classroom hours in students' classroom environments and at the end of the semesters these might be regarded as ways to minimize the location threat to internal validity.

Another internal validity threat of the current study was the possibility of existing counfounding variables. The data were collected from students with different grade levels. Therefore, grade level might be considered as possible confounding variables of the current study. However, preliminary analyses showed that students' grade levels did not distort the results of the current study.

3.9.2. External Validity Threats

External validity refers to the extent to which the results of the study can be generalized to other populations, conditions, experimenters, and so forth (Gravetter and Forzano, 2011). In the current study, the participants of the current study are from a highly prestigious university in Turkey. Therefore, it is possible that the participants of the study have different attitudes toward statistics than students in other universities in Turkey and than the students in other countries. This prevents the results being generalized to other populations. Therefore, the current study is limited to the participants of the study who were enrolled in statistics courses in a university in Turkey.

In addition, in the current study, attitudes toward statistics, self-reported mathematics achievement, and two of the item parcels of statistics outcomes variables (students' willingness to use statistics in the remainder of degree program and willingness to use statistics when employed) were the self-reports of participants. Therefore, the data collected in this study is limited to the participants' perceived levels of related constructs. Likewise, students' 'statistics grades' were obtained by using students' statistics letter grades. Accordingly, statistics grades variable cannot be generalized to students' overall statistics achievement.

Lastly, in the current study, all of the variables but students' statistics grades after taking statistics courses were measured at a single point in time. Therefore, the structural relationships proposed 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.

CHAPTER IV

RESULTS

This chapter presents the results of the study. The chapter is initiated with the data screening results in terms of missing data, influential outliers and necessary assumptions for further analyses. Next, descriptive analyses are presented to describe the participants of the study. Finally, results of the Structural Equation Modeling (SEM) analysis are presented in order to answer the research question of the study. The chapter ends with a summary of results.

4.1. Data Screening

Before running SEM, the data should be carefully screened for several characteristics. In the current study, firstly, negatively worded items were reversed to make the data ready for the subsequent analyses. Secondly, data were examined in terms of missing values, influential outliers, normality, linearity, homoscedasticity, and multicollinearity (Kline, 2005). SPSS 15 was used in order to test these assumptions.

4.1.1. Missing Data

In this study, all the variables except 'grade' variable (with 13.4% missing cases) had less than 2% missing cases (Appendix B). Missing value analysis was conducted to detect whether missingness was completely at random (MCAR). Little's Missingness Completely at Random (MCAR) test indicated that the missing data pattern was considered to be completely missing at random since the analysis resulted in a statistically non-significant chi-square value, $\chi^2(211) = 228.07$, $p = .20$. As the data were missing completely at random, two options for dealing with randomized missing values were possible in an SEM analysis: listwise deletion and imputation. Imputation refers to "the process of estimating the missing data of an observation based on valid values of other variables" (Hair et al., 1998). In the current study, an imputation method was used to deal with missing values; because, listwise deletion reduces the number of participants that might be less representative of the population. Consequently, in this study, an imputation method, maximum likelihood of estimation which is the most widely used estimation algorithm in Structural Equation Modeling, was used to replace the missing values (Kline, 2005).

4.1.2. Influential Outliers

Outliers are observations with a unique combination of characteristics identifiable as distinctly different from the other observations (Hair et al., 1998). A univariate outlier has an extreme score on a single variable, whereas a multivariate outlier has extreme scores on two or more variables. Box-plots were examined in order to search for univariate outliers for the variables entered into the Structural Equation Modeling equations. There were 22 univariate outliers (Appendix C). As SEM is a multivariate analysis, univariate outliers were not taken into consideration but multivariate outliers were of special importance. In order to examine the data in terms of multivariate outliers, Mahalanobis distance (Mahalanobis $D^{2)}$ was used. Mahalanobis D^2 is a measure of distance in multidimensional space of each observation from the mean center of multidimensional centrality (Hair et al., 1998). Only three cases were detected as multivariate outliers as they exceeded the critical value, $F(18,182) = 47.06$, $p<.01$ (Appendix C). There were no differences between the model fit indices when the analyses were generated with and without outliers. Therefore, the analyses were preceded with complete data set throughout the study.

4.1.3. Univariate and Multivariate Normality

The results of the tests used for univariate and multivariate normality assumptions were presented in Appendix C. Univariate normality of the data distribution was inspected by using Skewness (asymmetry), Kurtosis (peakedness) values, and the Quantile by Quantile plots (Q-Q plots) of the variables entered into SEM analyses. Plots revealed a 45-degree line, indicating that departures from normality were acceptable. Skewness and Kurtosis values were close to zero indicating that the distribution is close to normal (Tabachnick & Fidell, 2007). Mardia's test was used to examine multivariate normality. The test revealed a significant result indicating non-normal multivariate distribution. As a remedy, maximum likelihood estimation with robust standard errors (MLR) method, an estimation method used in SEM analyses which did not require multivariate normality, was used throughout the study (Muthen & Muthen, 2007).

4.1.4. 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 (Hair et al., 1998). Linearity and homoscedasticity are the aspects of multivariate normality that can be evaluated by the inspection of bivariate scatter plots (Kline, 2005). In the present study, inspection of bivariate scatter plots resulted oval-shaped array of points demonstrating that variables are linearly related and their variances are homogenously distributed.

4.1.5. Multicollinearity

Multicollinearity represents the degree to which any variable's effect can be predicted or accounted for by the other variables in the analysis (Hair et al., 1998). In this study, inter-correlations among item parcels ranged from .01 to .77 (Appendix D). Therefore, no multicollinearity problem was encountered, as these values did not exceed the critical value of .90 (Kline, 2005).

4.2. Descriptive Statistics

In this part, frequencies and percentages, means and standard deviations, and bivariate correlations among the variables are presented in order to describe participants' characteristics in terms of their mathematics achievement, expectancy of statistics success, statistics achievement, willingness to use statistics, and attitudes toward statistics. SPSS 15 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 bad) to 7 (very good). Of all the students (n=247), 2 (.8%) students rated their past achievement as 1 out of 7 (very bad); 2 (.8%) students rated as 2 out of 7; 7 (2.8%) students rated as 3 out of 7, 23 (9.3%) students rated as 4 out of 7 (neutral); 52 (21.1%) students rated as 5 out of 7; 67 (27.1%) students rated as 6 out of 7; and 92 (37.2%) students rated as 7 out of 7 (very good). That is, most of the participants (n=211, 85.4%) 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, none of the students rated their overall mathematics achievement as 1 out of 7 (very bad). Of all the students, 2 (.8%) rated their overall mathematics achievement as 2 out of 7, 4

(1.6%) students rated as 3 out of 7, 32 (13%) students rated as 4 out of 7 (neutral), 72 (29.1%) students rated as 5 out of 7, 82 (33.2%) students rated as 6 out of 7, and 50 (20.2%) students rated as 7 out of 7 (very good). These results indicated that most of the participants (n=204, 83.5%) 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

	Past Math Achievement		*Overall math achievement*	
Rating	*f*	%	*f*	%
1	2	.8	0	0
2	2	.8	2	.8
3	7	2.8	4	1.6
4	23	9.3	32	13
5	52	21.1	72	29.1
6	67	27.1	82	33.2
7	92	37.2	50	20.2
Missing	2	.8	5	2
Total	247	100	247	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, 9 (3.6%) students stated that they expected to get FF, 11 (4.5%) students expected to get FD, 18 (7.3%) students expected to get DD, 23 (9.3%) students expected to get DC, 31 (12.6%) students expected to get CC, 29 (11.7%) students expected to get CB, 49 (19.8%) students expected to get BB, 44 (17.8%) students expected to get BA, and 28 (11.35) students stated that they expected to get AA at the end of taking their current statistics courses (Table 4.2).

Table 4.2

Frequencies and Percentages for Expectancy of Success in Statistics Course

Expected grade	*f*	%
FF	9	3.6
FD	11	4.5
DD	18	7.3
DC	23	9.3
CC	31	12.6
CB	29	11.7
BB	49	19.8
BA	44	17.8
AA	28	11.3
Missing	5	2.0
Total	247	100

As seen in Table 4.2, of all the students 20 (8.1%) students were expecting to fail their statistics courses with FF or FD. More than half of the participants (n=150, 60.6%) were expecting to get statistics grades higher than CC and about half of the students (48.9%) were expecting to be successful in their statistics courses by getting statistics grades BB or higher.

4.2.3. Students' Statistics Achievement

Students' statistics achievement was measured by their total grades earned at the end of taking statistics course. The information of their grades was obtained from Student Affairs' Information System of the university after student affairs' registration office announced the grades. Students' grades ranged from DD (1 out of 7) to AA (7 out of 7). Descriptive analysis revealed that participants of the study had, approximately, an average achievement of statistics ($M = 4.86$, $SD = 1.97$) at the end of taking statistics courses.

4.2.4. Students' Willingness to Use Statistics

Frequencies and percentages are presented in order to portray 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 = 247)

	Willingness to Use Statistics			
	Remainder of Program of Study		*When Employed*	
Ranking	*f*	%	*f*	%
1	11	4.5	10	4.0
2	13	5.3	16	6.5
3	30	12.1	27	10.9
4	53	21.5	56	22.7
5	50	20.2	59	23.9
6	47	19.0	49	19.8
7	38	15.4	27	10.9
Missing	5	2.0	3	1.2

Of all the students, 11 (4.5%) rated their use of statistics in the remainder of their program of study as 1 out of 7 (not at all); whereas 13 (5.3%) students rated as 2 out of 7, 30 (12.2%) students rated as 3 out of 7, 53 (21.5%) students rated as 4 out of 7 (neutral), 50 (20.2%) students rated as 5 out of 7, 47 (19%) students rated as 6 out of 7, and 38 (15.4%) students rated as 7 out of 7 (a great deal). When students' were asked how much they would use statistics when they are employed, 10 (4%) students rated as 1 out of 7 (not at all), 16 (6.5%) students rated as 2 out of 7, 27 (10.9%) students rated as 3 out of 7, 56 (22.7%) rated as 4 out of 7 (neutral), 59 (23.9%) students rated as 5 out of 7, 49 (19.8%) students rated as 6 out of 7, and 27 (10.9%) students rated as 7 out of 7 (a great deal).

As seen in Table 4.3, more than half of the students (n = 135, 54.6%) were willing to use statistics in the remainder of their degree program, when about 1/5 of the students (n = 54, 21.9%) were not willing to use statistics in the remainder of their degree program, and about the same number of students (n = 53, 21.5%) were neutral about using statistics in the remainder of their degree program.

Similarly, more than half of the students (n = 135, 54.6%) were willing to use statistics when they are employed when about 1/5 of the students (n = 53, 21.4%) were not willing to use statistics when they are employed, and about the same number of students (n = 56, 22.7%) were neutral about using statistics when they are employed. In sum, more than half of the students were willing to use statistics in the remainder of their degree program and when they are employed.

4.2.5. Students' Attitudes Toward Statistics

Means and standard deviations are presented in order to examine students' attitudes toward statistics. Mean and standard deviation 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 affect (M = 4.60, SD = 1.38), cognitive competence (M = 5.43, SD = 1.07), value (M = 5.02, SD = 1.02), and effort (M = 5.10, SD = 1.27).

In terms of interest (M = 4.37, SD = 1.57) and difficulty subscales (M = 3.52, SD = .88) they had neutral attitudes toward statistics. These results were consistent with previous findings. Data collected from the students from Netherlands (Tempelaar et al, 2007), United States (Carlson & Winquist, 2011;

Carnell, 2008; Mills, 2004), and South Africa (Coetzee & van der Merwe, 2010) revealed similar results that students generally had neutral or positive attitudes toward statistics at the end of taking statistics courses. The mean and standard deviation values for SATS-36© subscales are presented in Table 4.4.

Table 4.4

Means and Standard Deviations for Attitudes toward Statistics (n = 247)

SATS-36© Components	*M*	*SD*
Affect	4.60	1.38
Cognitive Competence	5.43	1.07
Value	5.02	1.02
Difficulty	3.52	.88
Interest	4.37	1.57
Effort	5.10	1.27

4.2.6. Correlations Among Variables

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

Table 4.5

Correlations Among Variables (*n* = 247)

	1	2	3	4	5	6	7	8
1. Affect	1							
2.Cognitive Competence	.68*	1						
3. Value	.43*	.36*	1					
4. Difficulty	.48*	.41*	.10	1				
5. Interest	.62*	.40*	.66*	.05	1			
6. Effort	.26*	.18*	.28*	-.13*	.49*	1		
7. Statistics Outcomes	.38*	.35*	.51*	.01	.57*	.44*	1	
8. Math Achievement	.06	.07	.07	.03	.02	-.02	.14*	1

*p<.05

The strength of correlation is often categorized as weak, moderate, or strong. However, there is no agreement on what these terms mean (Veaux, Velleman, & Bock, 2006). In the current study, the criterion used by Field (2005), and Coolidge (2006) 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 and all of the attitudes toward statistics variables but difficulty were statistically significant. The statistically significant correlations were positive. The correlations among statistics outcomes and cognitive competence ($r = .35$, $p<.05$), effort ($r = .44$, $p<.05$), and affect ($r = .38$, $p<.05$) were moderate and statistically significant; correlations among statistics outcomes and value ($r = .51$, $p<.05$) and interest ($r = .57$, $p<.05$) were strong and statistically significant.

However, the correlation between statistics outcomes and difficulty was not statistically significant ($r = .01$, $p>.05$), indicating that statistics outcomes are not dependent on students' perceptions about the difficulty of statistics as a subject. These results showed that students' scores on statistics outcomes were higher when they reported high cognitive competence, effort, affect, value, and interest scores. That is, the more students had positive affect toward statistics, felt cognitive competence, valued statistics, were interested in statistics, and spent effort to learn statistics the higher their scores on statistics outcomes were.

There was a positive and statistically significant but low correlation between mathematics achievement and statistics outcomes ($r = .14$, $p<.05$); but, there was no statistically significant correlation between math achievement and any one of the attitudes toward statistics variables. This result indicated that students who reported high math achievement scores had high statistics outcomes scores, although this relationship was low; and students' attitudes towards statistics were not related to their self-reported mathematic achievement.

There were strong, statistically significant, and positive correlations between affect and cognitive competence ($r = .68$, $p<.05$), affect and interest ($r = .62$, $p<.05$), value and interest ($r = .66$, $p<.05$), indicating that students who reported that they like statistics also reported that they felt cognitive competence and interest in statistics. Students who reported that they were interested in statistics reported that they valued statistics.

There were moderate, statistically significant, and positive correlations between value and affect ($r = .43$, $p<.05$), difficulty and affect ($r = .48$, $p<.05$), value and cognitive competence ($r = .36$, $p<.05$), difficulty and cognitive competence ($r = .41$, $p<.05$), interest and cognitive competence ($r = .40$, $p<.05$), and effort and interest variables ($r = .49$, $p<.05$). These results indicated that students who reported that they like statistics also reported that they valued statistics and thought that statistics was an easy subject. Students who reported that they felt cognitive competence in statistics also reported that they valued statistics; they thought that statistics was an easy subject, and they were interested in statistics. Students who reported that they were interested in statistics also reported that they devoted effort to learn statistics.

There were statistically significant but low correlations between effort and affect ($r = .26$, $p<.05$), cognitive competence ($r = .18$, $p<.05$), value ($r = .28$, $p<.05$), and difficulty ($r = -.13$, $p<.05$). That is, students who reported that they devoted effort on learning and using statistics also reported that they like, felt cognitive competence in statistics, valued statistics and found statistics as an easy subject. In addition, the correlations between value and difficulty ($r = .10$, $p>.05$), and interest and difficulty ($r = .05$, $p>.05$) variables were not statistically significant, indicating that students valuing of statistics and their individual interest in statistics were independent of their perceptions of the difficulty of statistics as a subject.

4.3. Preliminary Analysis

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

Table 4.6
Means and Standard Deviations for Attitudes Toward Statistics by Grade Levels (*n*=236)

Components	undergraduate						graduate			
	2th year (n=89)		3th year (n=52)		4th year (n=15)		master (n=57)		PhD (n=23)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
cognitive	5.24	1.02	5.50	1.07	5.44	.99	5.67	1.14	5.23	.95
value	4.72	.99	4.90	1.14	5.11	.87	5.35	1.06	5.51	.58
difficulty	3.47	.83	3.78	.91	3.76	1.12	3.31	.76	3.33	.95
interest	3.77	1.56	4.13	1.36	4.08	1.28	5.12	1.53	5.47	.98
effort	4.75	1.17	4.79	1.37	4.84	1.54	5.77	1.09	5.59	1.02
affect	4.27	1.37	4.83	1.34	4.53	1.41	4.75	1.38	4.75	1.07

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

Prior to the analysis, homogeneity of variances among groups was assessed. Except value component, 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, 2005). For the value component, alpha level was set to .001, as the group variances were significantly different.

The results of the ANOVA revealed that students' interest in statistics, $F(4,231)=11.56$, $p<.025$, and effort they spent to learn statistics, $F(4,231)=8.21$, $p<.025$, were significantly different for the students from different grade levels. However, when the strength of the associations were investigated, effect sizes were small for interest and effort components. In other words, grade level had small effect on students' interest in statistics, $\eta^2 = .019$, and on effort they spent to learn statistics, $\eta^2 = .007$.

When pairwise comparisons were examined, it was found that from ten pairwise comparisons, four comparisons were statistically significant for interest variable and two comparisons were statistically significant for effort variable. In sum, it was assumed that students' coming from different grade 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, the eight-factor confirmatory factor analysis

(CFA) model was examined to test the measurement model. In the second step, the model with a structural portion was examined.

Maximum likelihood parameter estimates with standard errors and a chi-square test statistics that are robust to non-normality (MLR) was used as an estimation method (Muthen & Muthen, 2007) in order to test the measurement and structural portion of the hypothesized structural regression model. Mplus student version 5.21 was used for SEM analyses.

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 (item parcels) were tested in an eight factor measurement model by using a confirmatory factor analysis technique. Multiple criteria were used to interpret the results of the measurement model tested by Confirmatory Factor Analysis (CFA).

Firstly, measures of overall fit were examined considering several indices. Secondly, parameter estimates were examined to ensure that they are in the right direction and of reasonable size. Thirdly, latent factor correlations were inspected, and fourthly, factor determinacies were examined. Lastly, standardized residuals were examined to determine whether there were any aspects of the model that did not fit the data well (Dilalla, 2000). The tested measurement model is presented in Figure 4.1.

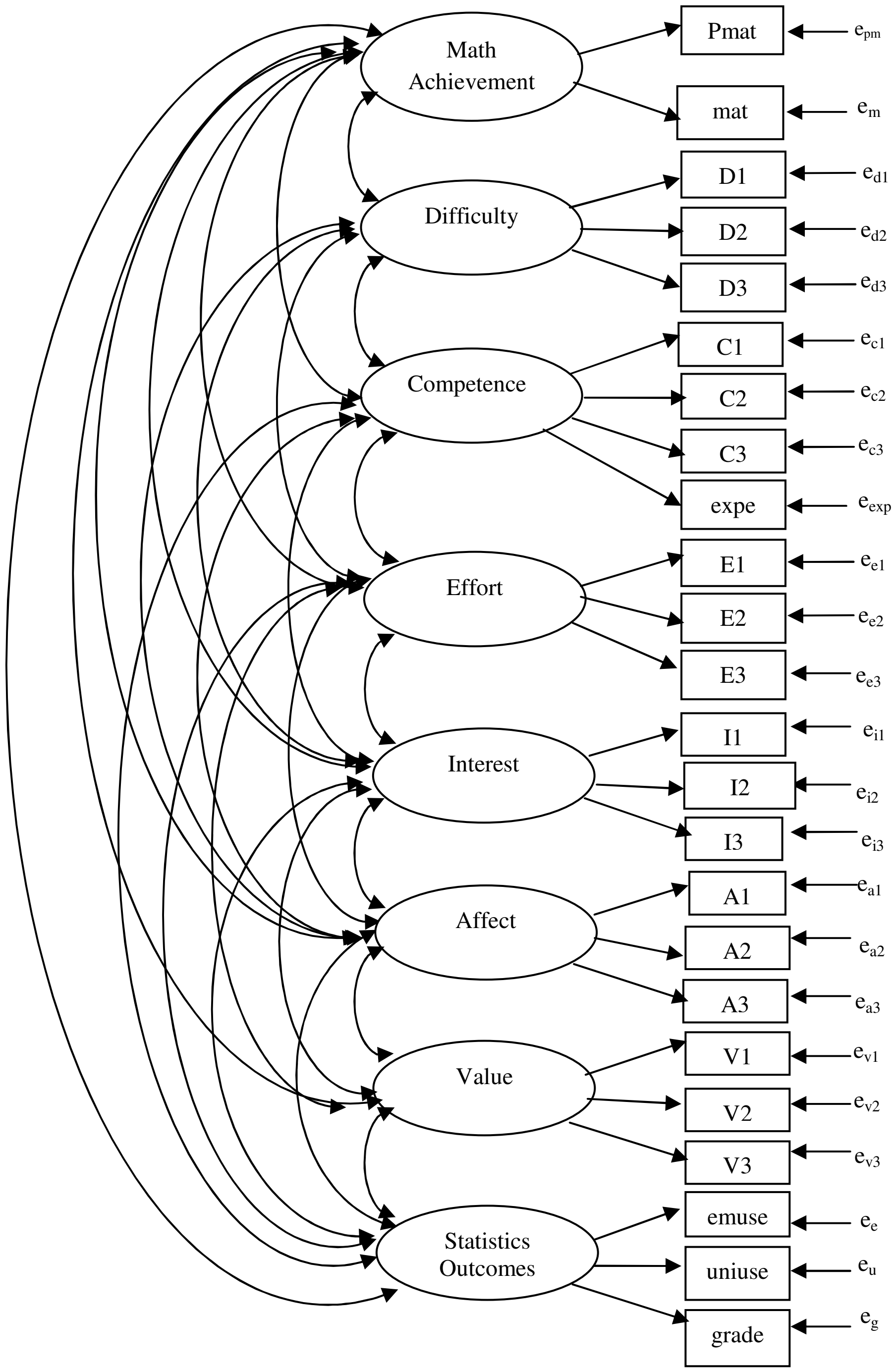


Figure 4.1 Measurement Model

Note: A1-A3: Affect item parcels, Competence: Cognitive Competence, C1-C3: Cognitive Competence item parcels, V1-V3: Value item parcels, D1-D3: Difficulty item parcels, E1-E3: Effort item parcels; I1-I3: Interest item parcels, expe= Expectancy of Success, p_{mat}=Previous Math Achievement, mat=Overall math achievement, emuse= willingness to use statistics when employed, uniuse= willingness to use statistics in the remainder of the degree program

Several model fit indices were inspected to examine the measures of overall model fit (MacCallum et al., 1996). In addition to model chi square, normed chi square (χ^2/df), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) fit indexes were inspected in this study. The chi square value was significant χ^2 (224) = 387.163, p=.00, indicating that the model predicted relations that were significantly different from the relations observed in the sample. The normed chi square (χ^2/df) was used to correct for the sample size sensitivity of the model chi square. The normed chi square value, which was 1.73, indicated a reasonable fit as values close to 2 have been recommended as demonstrating reasonable fit (Kline, 2005). Consistently, CFI= .93, indicated reasonably good fit of the model to the data as suggested by Marsh, Hau, and Wen (2004). SRMR=.06 and RMSEA=.05 with the 90 percent confidence interval of .05 to .06 also indicated close approximate fit of the model (Kline, 2005; MacCallum, Browne, & Sugawara, 1996). In sum, values of the selected fit indices consistently indicated that hypothesized measurement model fits the data well. In addition to the model fit indices, path coefficients were examined to interpret the results of the CFA. Unstandardized estimates of the path coefficients are interpreted as unstandardized regression coefficients that estimate the direct effects of the factors on indicators. The unstandardized path coefficients of the CFA model are presented in Appendix E. The unstandardized coefficients showed that all the indicators' loadings on their respective latent variables were statistically significant. Standardized path coefficients are analogous to beta weights in regression. The standardized path coefficient values less than .10 indicate small effect; values around .30 indicate medium effect; and values greater than .50 indicate large effects (Kline, 2005). In the current study, standardized factor loadings were all statistically significant and ranged from .24 (medium) to .91 (large). The results revealed from path coefficients demonstrated that the indicators (item parcels) represented in the model were well explained by the corresponding factors (Figure 4.2).

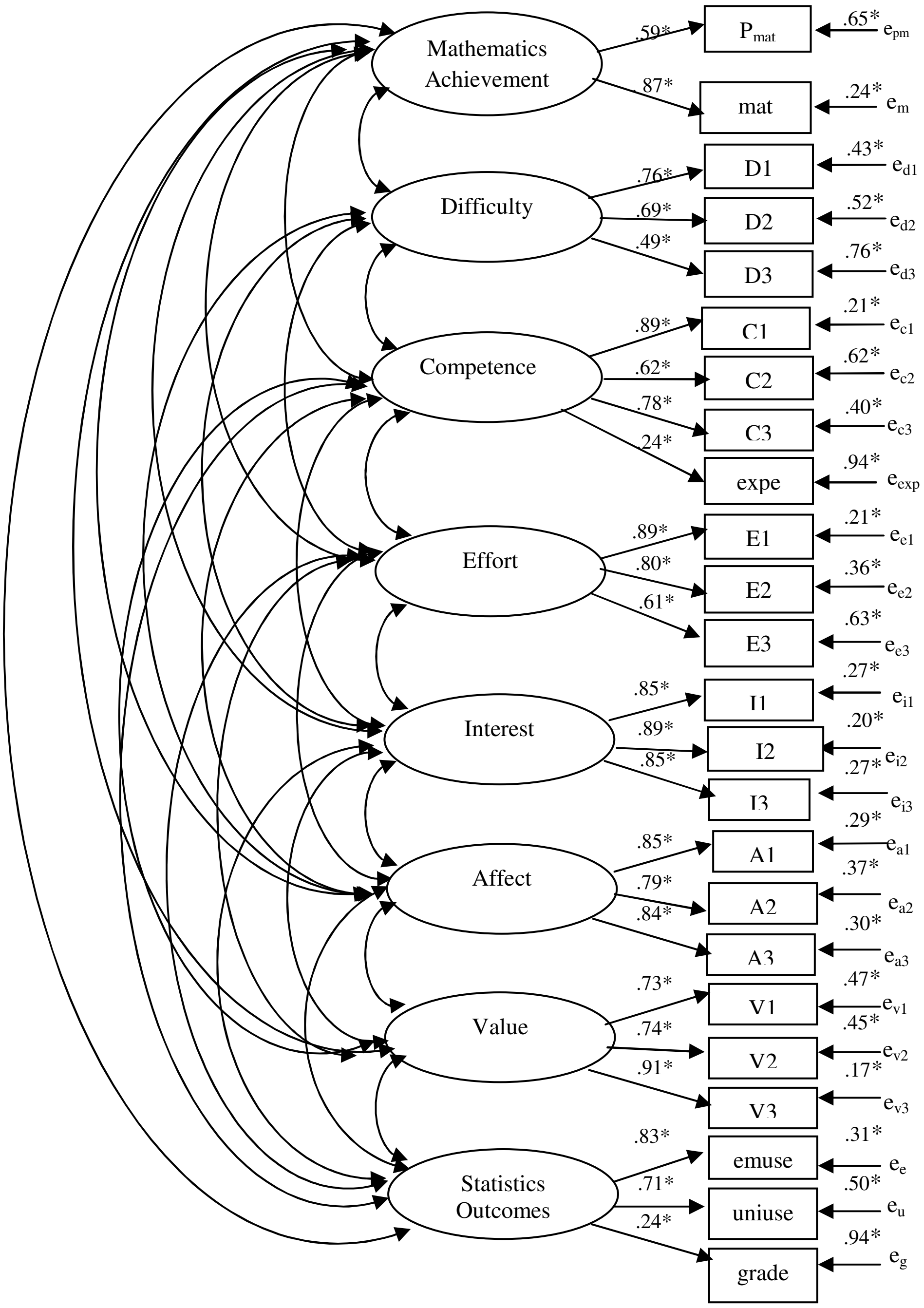


Figure 4.2 Standardized Path Coefficients in Measurement Model

Note: **p*<.05, A1-A3: Affect item parcels, Competence: Cognitive Competence, C1-C3: Cognitive Competence item parcels, V1-V3: Value item parcels, D1-D3: Difficulty item parcels, E1-E3: Effort item parcels; I1-I3: Interest item parcels, expe= Expectancy of Success, p_{mat}=Previous Math Achievement, mat=math achievement, emuse= willingness to use statistics when employed, uniuse= willingness to use statistics in the remainder of the degree program

In order to interpret the tested measurement model, factor correlations were also taken into consideration. The results revealed that 19 out of 28 correlations were statistically significant. Most of the significant correlations were low or moderate. Statistically low and moderate as well as non-significant associations suggested discriminant validity. That is, the latent variables in the model were empirically distinguishable. However, the correlation between cognitive competence and affect was very strong ($r = .85$, $p<.05$). This amount of strong correlation could cause multicollinearity; but, this amount of association was expected since previous studies reported such high correlation between cognitive competence and affect latent variables (Dauphinee, 1997; Hilton et al., 2004; Tempelaar et al., 2007). Moreover, it was reported that cognitive competence and affect were theoretically distinct constructs (Hilton et al, 2004). Therefore, cognitive competence and affect variables were accepted as distinct variables in the current study. The correlation coeffiencts between estimated latent variables are presented in Table 4.7.

Table 4.7

Estimated Latent Variable Correlations (n = 247)

	1	2	3	4	5	6	7	8
1.Math achievement	1	.06	.16*	.03	.07	.10	.08	26*
2.Difficulty		1	.67*	-.14	.07	.62*	.10	-.05
3.Cognitive competence			1	.24*	.57*	.85*	.50*	.37*
4.Effort				1	.54*	.30*	.30*	.44*
5.Interest					1	.69*	.76*	.70*
6.Affect						1	.47*	.39*
7.Value							1	.73*
8.Statistics outcomes								1

*$p<.05$

In order to examine how well the latent variables were measured by observed variables, factor determinacies were inspected. Factor determinacies are the proportion of variance in each factor explained by the observed variables. Higher proportions of variance explained indicate better fit (UCLA Academic Technology Services, no date). In the current study, factor determinacy values ranged from .89 to .96, demonstrating that, overall, the factors of the measurement model were measured well (Dilalla, 2000). Factor determinacies for the measurement model are presented in Table 4.8.

Table 4.8

Factor Determinacies (n = 247)

Factors	*Factor determinacy values*
Math achievement	.89
Difficulty	.90
Cognitive competence	.95
Effort	.93
Interest	96
Affect	.95
Value	.95
Statistics outcomes	.91

Lastly, standardized residuals for covariances/correlations were examined in order to investigate whether there were any aspects of the model that did not fit the data well. The results revealed that standardized residuals were not high, indicating that the measurement model was adequately accounting for the covariance/correlation among the variable pairs (Appendix F).

4.4.2. Structural Regression Model

Multiple criteria were used to interpret the Structural Regression model. In order to interpret the overall fit of the hypothesized “Statistics Attitudes-Outcome Model” to the data of the current study, several model fit indices were examined. These were chi-square, normed chi-square, CFI, SRMR, and RMSEA. In addition, parameter estimates were examined to interpret the effecs on endogenous variables from other variables presumed to directly predict them. Next, the indirect and total effects were examined to interpret the effects on dependent variable (statistics outcome) from other variables through indirect and all presumed ways, respectively. Lastly, squared multiple correlation coefficients were examined to investigate the amount of variance in each latent variable that was explained by the model.

The chi-square value was significant $\chi^2(235) = 409.761$, $p<.05$, indicating that the model predicted relations that were significantly different from the relations observed in the sample. However, as stated earlier, many problems have been reported related to χ^2 as a fit statistics. Therefore, several other model fit indices were examined in terms of their consistency with each other. The normed chi-square value was 1.74, indicating a reasonable fit. Consistently, CFI = .93, indicated reasonably good fit of the model to the data. SRMR = .07 and RMSEA=.06 (90 % CI = .05-.06) also indicated close approximate fit of the model (Kline, 2005). In sum, values of the selected fit indices consistently indicated that hypothesized structural regression model fitted the data well.

Results indicated that the standard errors of the parameters (S.E.) ranged from .05 to .28, indicating that the estimates were reasonably determined (Appendix G). In addition, all factor loadings of the measurement portion were statistically significant, and ranged from .23 (medium) to .90 (large). That is, indicator variables were significantly explained by their corresponding latent variables.

The standardized parameter estimates for the structural portion of the model revealed ten out of sixteen statistically significant coefficients, indicating that ten of the sixteen presumed direct effects on endogenous variables from other variables were statistically significant. The statistically significant coefficients ranged from γ = .20 (small effect) to γ = .86 (large effect). The six non-significant coefficients were the direct effects from math achievement to cognitive competence and affect, cognitive competence to effort, affect to value; and cognitive competence and affect to statistics outcomes. The standardized parameter estimates are presented in Figure 4.3.

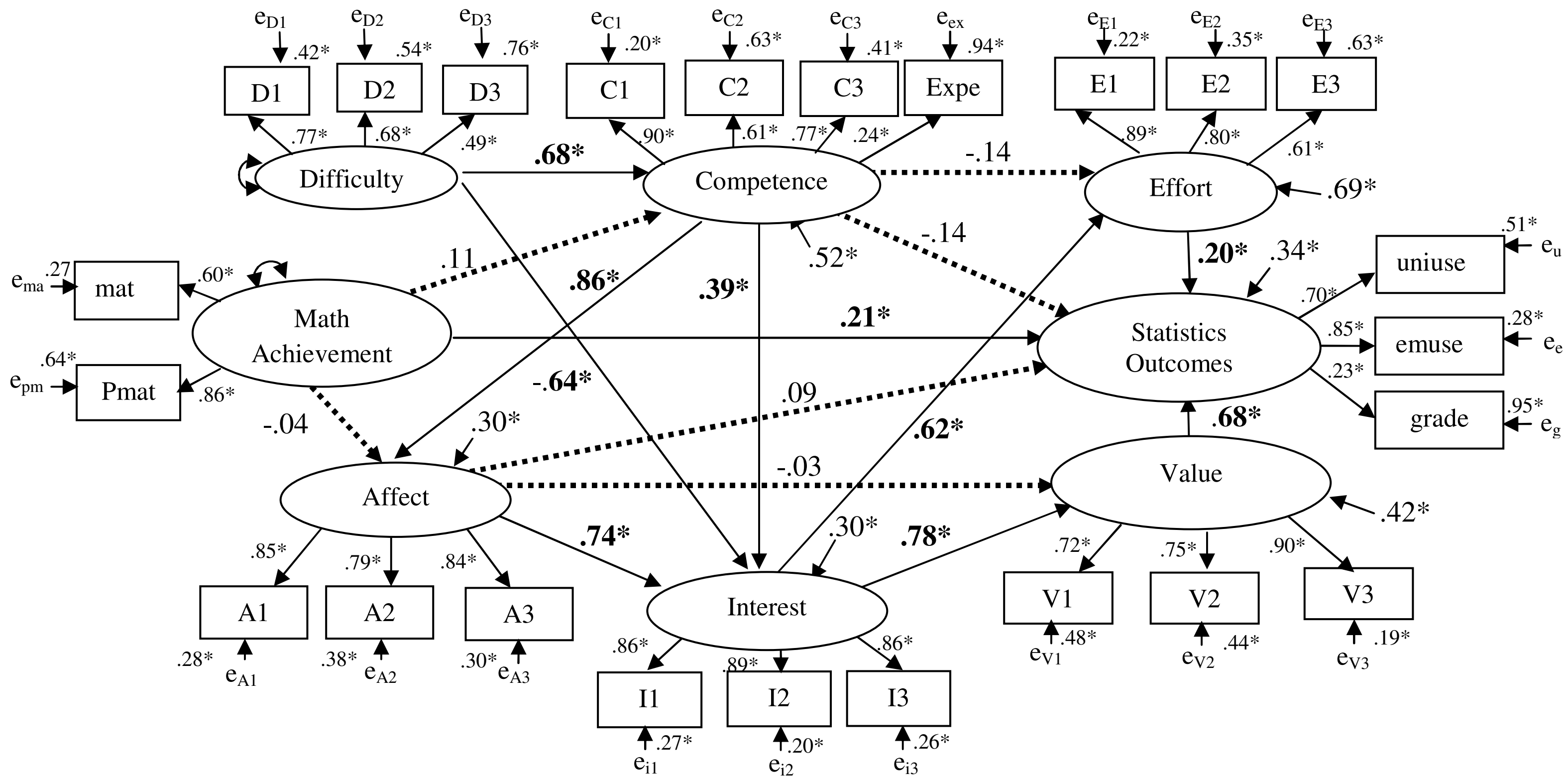


Figure 4.3 The Standardized Values of the Hypothesized Model Fit, - - -➝ presents non-significant paths, ⟶ presents statistically significant paths, *p<.05. Note: A1-A3: Affect item parcels, Competence: Cognitive Competence, C1-C3: Cognitive Competence item parcels, V1-V3: Value item parcels, D1-D3: Difficulty item parcels, E1-E3: Effort item parcels; I1-I3: Interest item parcels, expe= Expectancy of Success, p_{mat}=Previous Math Achievement, mat=Overall math achievement, emuse= willingness to use statistics when employed, uniuse= willingness to use statistics in the remainder of the degree program

Results revealed that mathematics achievement, effort and value had statistically significant direct effects on statistics outcomes variable. The direct effects of effort (γ = .20, $p<.05$) and mathematics achievement (γ = .21, $p<.05$) on statistics outcomes were small when the direct effect of value (γ = .68, $p<.05$) on statistics outcomes was large. That is, when students had higher self-reports of mathematics achievement, spent more effort in statistics courses, and valued statistics they had higher statistics outcomes at the end of their statistics courses. This result also demonstrated that value had more contribution than effort and mathematics achievement with regard to explaining students' statistics outcomes. On the other hand, interest had statistically significant direct effects on effort and value variables. The direct effects of interest on effort (γ = .62, $p<.05$) and on value (γ = .78, $p<.05$) were both positive and large. 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, difficulty, and affect had statistically significant direct effects on interest variable. The direct effect of difficulty on interest was negative and large (γ = -.64, $p<.05$), indicating that students who perceived statistics as an easy subject were less interested in statistics. However, the direct effect of affect on interest was positive and large (γ = .74, $p<.05$), indicating that students who had positive feelings about statistics were interested in statistics. The direct effect of cognitive competence on interest was positive and medium (γ = .39, $p<.05$). 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 (γ = .86, $p<.05$), indicating that when students had high cognitive competence in statistics they had more positive feelings toward statistics. In turn, difficulty had statistically significant direct effect on cognitive competence. The direct effect of difficulty on cognitive competence was also positive and large (γ = .68, p<.05), indicating that when students perceive statistics as an easy subject their cognitive competence in statistics were high. Taken together, these results demonstrated that when students perceive statistics as an easy subject they had higher competence, and accordingly they had positive feelings about statistics.

Beside the direct effects, several total indirect effects were found to have statistically significant contribution to the prediction of statistics outcomes variable (Table 4.8). Although affect had no statistically significant direct effect on statistics outcomes variable, it had medium (.46) and statistically significant total indirect effect on statistics outcomes. More specifically, the indirect effect of affect on statistics outcome through interest and value was medium (.39) and statistically significant (Appendix H). That is, when students had positive feelings toward statistics, they were interested in statistics and therefore they valued statistics and they had higher statistics outcomes at the end of taking statistics courses. Like affect, cognitive competence had statistically significant total indirect effect on statistics outcomes variable, even though its direct effect was not statistically significant. The total indirect effect of cognitive competence on statistics outcomes was large (.70). The statistically significant indirect effect of cognitive competence on statistics outcomes was through the paths of affect, interest, and value and medium (.33) (Appendix H). That is, when students had higher cognitive competence in statistics they had more positive feelings about statistics, which resulted with their high interest in statistics. The more they were interested in statistics they valued statistics; and therefore, they had higher statistics outcomes. Lastly, interest had statistically significant and large total indirect effect on statistics outcomes (.65). The indirect effect of interest on statistics outcomes through value was large (.53) and statistically significant. However, its indirect effect on statistics outcomes through effort was small (.12) but statistically significant. This result showed that when students were interested in statistics their valuing of and spending effort on statistics was getting higher, and they got higher statistics outcomes. This result also demonstrated that the indirect effect of interest on statistics outcomes though value had more contribution to predict statistics outcomes than that of effort. The summary of the direct, total indirect and total effects are presented in Table 4.9.

Table 4.9

Standardized Direct, Total Indirect and Total Effects (n = 247)

		Affect	Cognitive comp.	Interest	Effort	Value	Statistics outcomes
Mathematics achievement	Direct Effects	-.04	.11	-	-	-	.21*
	Total Indirect	.09	-	.01	-.02	.00	.04
	Total Effects	.05	.11	.01	-.02	.00	.25*
Difficulty	Direct Effects	-	.68*	-.64*	-	-	-
	Total Indirect	.58*	-	.69*	-.49*	-.50*	-.10
	Total Effects	.58*	.68*	.05	-.49*	-.50*	-.10
Affect	Direct Effects	-	-	.74*	-	-.03	.09
	Total Indirect	-	-	-	.46*	.58*	.46*
	Total Effects	-	-	.74*	.46*	.55*	.55*
Cognitive competence	Direct Effects	.86*	-	.39*	-.14	-	-.14
	Total Indirect	-	-	.64*	.64*	.28	.70*
	Total Effects	.86*	-	1.03*	.50*	.28	.56*
Interest	Direct Effects	-	-	-	.62*	.78*	-
	Total Indirect	-	-	-	-	-	.65*
	Total Effects	-	-	-	.62*	.78*	.65*
Effort	Direct Effects	-	-	-	-	-	.20*
	Total Indirect	-	-	-	-	-	-
	Total Effects	-	-	-	-	-	.20*
Value	Direct Effects	-	-	-	-	-	.68*
	Total Indirect	-	-	-	-	-	-
	Total Effects	-	-	-	-	-	.68*

*$p<.05$

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, 2005). 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 affect, cognitive competence, interest and value on statistics outcomes were large. More specifically, affect, cognitive competence, interest and value had total standardized effects on statistics outcome as .55, .56, .65 and .68 respectively. However, the total standardized effects of mathematics achievement and effort on statistics outcomes were medium, respectively .25 and .20. Only the total standardized effect of difficulty on statistics outcomes was small and statistically non-significant. This result demonstrated that, affect, cognitive competence, interest, and value variables had the biggest contribution to predict statistics outcomes through their all presumed pathways. In addition, mathematics achievement and effort variables had medium contribution to predict statistics outcomes through their all presumed pathways. However, difficulty had no statistically significant contribution to explain statistics outcomes through all its presumed ways, since the direct and indirect effects of the difficulty were in opposite directions.

In order to examine the amount of variance in each latent variable that was explained by the model, the squared multiple correlation (R^2) coefficients for latent variables were inspected. The results showed that the hypothesized model explained statistically significant amount of variance for each latent variable. The overall model explained 66% of the variance in statistics outcomes variable. The overall model also explained 58% of the variance in value, 31% of the variance in effort, 70% of the variance in interest, 48% of the variance in cognitive competence, and 73% of the variance in affect, all statistically significant (Table 4.10).

Table 4.10

Squared Multiple Correlations for Latent Factors (n = 247)

Variable	*Estimate*	*S.E.*
Outcome	.66*	.09
Value	.58*	.06
Effort	.31*	.06
Interest	.70*	.07
Cognitive Competence	.48*	.07
Affect	.73*	.07

*p<.05

4.5. Summary of the Results

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 expected 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 interest in statistics. At the end of taking statistics courses, they had an average grade of statistics. Descriptive results also demonstrated that students' scores from different attitudes toward statistics variables generally correlated with each other. Math achievement was significantly related to statistics outcomes but not to the attitudes toward statistics variables. All of the statistics attitudes variables except difficulty significantly correlated with statistics outcomes.

Structural equation modeling analyses indicated that all of the indicators in the model were explained by their corresponding factors significantly. The measurement and structural regression models fitted the data well. 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. Overall, the hypothesized structural regression model explained large amount of variance, 66% , in statistics outcome variable.

CHAPTER V

DISCUSSION

This chapter presents the discussions and implications of the results of the current study. In the first part of this chapter, the results of the study are discussed with regard to the existing literature. In the second part of the chapter, implications of these results are presented to provide suggestions for further research and for the practice of statistics education.

5.1. Discussion of Results

"Statistics cannot prove anything beyond a doubt"
S.R. Jammalamadaka, 1998

The purpose 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, which is 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. Statistically significant amount of variance was explained by the hypothesized model for each latent variable. Overall, the model explained large amount of variance (66%) in statistics outcomes variable. In addition to the overall model fit, the contribution of each latent variable for the explanation of the model was taken into consideration. Interest and value variables had the highest and statistically significant total effects on statistics outcomes via all their presumed pathways. Affect and cognitive competence latent variables had the second highest and statistically significant total effects on statistics outcomes via all their presumed pathways. Next, effort and mathematics achievement had medium and statistically significant total effects on statistics outcomes via all their presumed pathways. Difficulty was the only variable that had no statistically significant total effect on statistics outcomes via all its presumed pathways.

These results indicated that students' statistics outcomes, which were assessed by their statistics grades and willingness to use statistics after taking statistics courses were strongly predicted by students' personal interests in statistics and by the extent they value statistics. The more they were interested in statistics and the more they had positive attitudes toward the value of statistics they had higher statistics outcomes, which means that they earned higher statistics grades at the end of taking statistics course and they were willing to use statistics in the future. In addition, students' cognitive competence in statistics and affect toward statistics were found as important factors for explaining their statistics outcomes followed by the effort they expand to learn statistics and their self-reported mathematics achievement. That is, students who were having positive feelings about statistics and having high cognitive competence in statistics had higher statistics outcomes at the end of their statistics courses. In addition, when students had high perceptions of their past and overall mathematics achievement and spent effort to learn statistics, they got higher statistics grades and became more willing to use statistics in the future. Although the total effect of students' perceptions about the difficulty of statistics was not statistically significant in the tested model, it was statistically significant for explaining students' affect toward statistics, cognitive competence in statistics, effort devoted to learn statistics, and attitudes toward the value of statistics. Therefore, it is plausible to conclude that each variable presented in the model had important roles for explaining statistics outcomes and for explaining the overall model.

The results of the current study revealed both consistent and contrary findings with regard to the proposed "Statistics Attitudes-Outcomes Model", and to the existing literature.

Results 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 Eccles' Model; because, Eccles and her colleagues proposed that relative cost (spent effort) was the determinant of students' achievement related choices and performances (Eccles and Wigfield, 2002). Moreover, this finding was in line 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=1458) in Netherlands. Similarly, value variable had statistically significant direct effect on statistics outcomes, which supported the "Statistics Attitudes-Outcomes Model". Like the direct effect of effort, the direction of the direct effect of value was positive but large, which means that value variable had more contribution than the effort variable to the prediction of statistics outcomes. The positive direction of this effect showed that the more participants valued statistics the higher their statistics outcomes were. This finding was consistent with Eccles' Model. In Eccles' Model, it is proposed that subjective task value is an important determinant of achievement choices of individuals (Eccles & Wigfield, 2002; Wigfield & Eccles, 2000, 2002). Further, this finding was also in line with Tempelaar et al.'s (2007) study as they reported statistically significant direct effect of value on statistical reasoning (which is one of the learning outcomes of the statistics courses) scores for undergraduate economics and business students (n=1458), in Netherlands. However, Sorge and Schau (2002) reported that the direct effect of value on statistics achievement was not statistically significant for undergraduate engineering students (n=264) in U.S.A. Comparing these three studies, it is obvious to see that the participants of these studies are highly diverse with regard to their nationalities and departmental affiliations. Therefore, it is possible to state that engineering students in U.S.A differed from the other studies in terms of the structure of the relationship between value and statistics outcome variables. They might have highly succeeded in statistics even though they did not appreciate the value of statistics. Lastly, self-reported mathematics achievement variable had statistically significant direct effect on statistics outcomes, which was small and positive. 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 was also supported by earlier studies (Nasser, 2004; Sorge & Schau, 2002; Väisänen, Rautopuro, & Ylönen, 2004; Wisenbaker et al., 2000). However, surprisingly, in the present study, the direct effect of mathematics achievement on cognitive competence and affect were not statistically significant, which is contrary to proposed "Statistics Attitudes-Outcomes Model". Compared to the theoretical framework, there occurred some interesting points that need to be considered. Self-efficacy theory proposes that individuals' self-efficacy is a function of their prior beliefs about the task and their experience (Bandura & Schunk, 1981). In addition, Eccles' Model assumes that previous achievement related experiences affect individuals' affective memories (Eccles, 2005; Wigfield & Eccles, 2000). However, in this study, students' cognitive competence and affect toward statistics were not dependent on students' self-reports of their mathematics achievement. This finding might stem from the fact that self-efficacy theory and Eccles' Model propose the impact of previous experiences on individuals' affective memories and self-efficacy; however, in the current study, self-reported mathematics achievement involves both past and overall self-reports of mathematics achievement. As mathematics and statistics are related but distinct disciplines, students' previous and overall mathematics achievement are not the same as their previous achievement related experiences in statistics. Therefore, it may not be so easy to say that the finding of the study completely contradicts to the theoretical background. Further, the findings of the current study were in line with Nasser (2004) as she reported similar results by collecting data from Arabic speaking pre-service teachers (n=162) in Israel. She found no significant direct effect of mathematical aptitude (measured by number of mathematics units studied by the student and his/her rescaled high school mathematics grade) on attitudes toward statistics, but she found statistically significant direct effect of mathematics aptitude on statistics achievement. Consistent with Nasser's (2004) study, the findings of the current study showed that the participants of the current study who thought that they were high or low mathematics achievers did not differ in terms of their cognitive competence in statistics and in terms of their affect toward statistics; but, they differed in terms of their statistics outcomes. These results suggested that students' cognitive competence and affect toward statistics are independent of self-reports of mathematics achievement. From this point of view, the current study suggests that in order for students to have high cognitive competence and positive affect toward statistics, they do not have to report high achievement levels in mathematics. These results were in line with the argument of Garfield and Ben-Zvi (2007). They claimed, "*Students who may not be strong in mathematics may work hard and enjoy statistics*" (Garfield & Ben-Zvi, 2007, pp.379-380).

The results of the study showed that interest had large and statistically significant direct effect on effort and 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 spent to learn statistics and the more they valued statistics. In Eccles' model, the variables of value, interest and effort are involved in subjective task value component (Eccles & Wigfield, 2002). However, in the hypothesized model of the current study subjective task value component was separated into effort, value, and interest variables as distinct constructs. By finding statistically significant direct effect of interest on effort and on value variables, the current study supported the investigation of the relationships among these constructs. Another important finding related to the role of interest variable in the model was the fact that interest mediated the relationship between cognitive competence and effort. That is, students' cognitive competence in statistics did not significantly predict the effort students expand to learn statistics; however, students' cognitive competence in statistics significantly predicted effort via increasing their personal interest in 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, and accordingly, they spent more effort to learn statistics. This finding supported the self-determination theory as the theory proposes that individuals' interests in certain subjects are facilitated by their competency beliefs, which in turn influences their self-initiation of effort and persistence (Deci & Ryan 2000). This finding is also in line with Eccles Model that the model suggests that self-concepts of abilities influence one's intrinsic value, which in turn influence the achievement related choices (Wigfield, Tonks, Klauda, 2009). Interest was also significantly predicted by the indirect effect of cognitive competence through affect. Taken together, these findings supported the "Statistics Attitudes-Outcomes Model" and the self-determination theory. The theory proposes that individuals' interests in certain subjects are facilitated by their competency beliefs and feelings of relatedness (Ryan & Deci, 2000; Schiefele, 1991;

Vallerand, 2000). In addition, this finding also supported Eccles' Model (Wigfield, Tonks, Klauda, 2009) as it proposes that one's intrinsic motivation and interest are facilitated by self-concepts of abilities and affective memories and individuals' affective reactions and memories influence their subjective task value (that includes interest and value components). In sum, the current study demonstrated that students' personal interest in statistics was predicted both directly by their cognitive competence in statistics and indirectly by the effect of cognitive competence on affect toward statistics. That is, when students had high cognitive competence in statistics that directly contributed them to get interested in statistics; moreover, when they had high cognitive competence they had positive feelings about statistics and therefore they were more interested in statistics.

Besides cognitive competence had statistically significant and medium direct effect on interest, it had positive, large, 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 more they had positive affect toward statistics. This finding was in line with Bude´ et al.'s (2007) study since they found statistically significant direct effect of outcome expectancy (students' beliefs regarding future success) on affect toward statistics in a sample of undergraduate health sciences students (n=94), in Netherlands. Despite the fact that cognitive competence had 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". Some of the earlier studies reported similar results. Bude´ et al. (2007) reported non-significant direct effect of outcome expectancy on effort. Sorge and Schau (2002) reported non-significant direct effect of cognitive competence on statistics achievement. However, Tempelaar et al. (2007), found statistically significant direct effect of cognitive competence on statistics exams and quizzes in a sample of economics and business students (n = 1458) in Netherlands. There might be several reasons for the inconsistent results in these three studies. Sorge and Schau (2002) conducted their study with engineering students, Bude´ et al. (2007) with health sciences students, and Tempelaar et al. (2007) with economics and business students. Another reason might be that, students' statistics achievement and statistics outcomes were assessed by different measures in these studies, and lastly these studies were conducted in different countries with different cultural groups. In addition, in the current study as interest variable placed between the cognitive competence and effort, it might have reduced the effect of cognitive competence on effort and on statistics outcomes. In the current study; although, the direct effect of cognitive competence on statistics outcomes and on effort was statistically non-significant, the direct effect of cognitive competence on affect and on interest were significant; which caused that cognitive competence had large and statistically significant total effects on effort and statistics outcomes. That is, despite not directly, students' cognitive competence in statistics had a significant role on contributing to the prediction of effort students expand to learn statistics and to the prediction of students' statistics outcomes. Comparing these findings to the theoretical framework, the findings of the current study are in line with the theoretical framework. Learning theories, self-efficacy and self-determination theories, and expectancy value theories propose that individuals' perception of their performance capabilities and expectancies for success are the determinants of their achievement and motivations in certain tasks.

In the current study, it was interesting to find that, the direct effects of affect on value and statistics outcomes were not statistically significant. This finding was contrary to the existing literature. Sorge and Schau (2002) reported statistically significant direct effect of affect on value and on statistics achievement for the undergraduate engineering students (n = 264) and Bude´ et al. (2007) reported statistically significant direct effect of affect on the statistics achievement for undergraduate health sciences students (n = 94). The previous studies used statistics achievement as dependent variable; whereas in the current study the dependent variable is statistics outcomes, as well as sample characteristics are highly different in these studies. In addition, the tested model in the current study is highly different from that of previous studies. In the current study, affect had indirect effect on value through its direct effect on interest. Likewise, affect had statistically significant indirect effect on statistics outcomes through its indirect effect on value, which is through interest. As a result, considering the total effects, the study revealed statistically significant total effects of affect on value and statistics outcomes. Therefore, the current study demonstrated that students' affect toward statistics is an important factor for explaining students' statistics outcomes and the value students attributed to statistics. This relationship was also positive. That is, the more students had positive affect toward statistics the more they were interested in statistics, valued statistics and the more they scored higher in terms of statistics outcomes. From this point of view, it is not wrong to suggest that the current study is consistent with Eccles' Model as the model suggests that affective memories influence subjective task values, which in turn influence achievement-related choices and performances (Eccles, 1994; Wigfield & Eccles, 2000; 2002).

Another interesting finding was that the direct and indirect effects of difficulty on interest were in opposite directions. Difficulty had large and statistically significant direct effect on cognitive competence and on interest. This finding was consistent with the "Statistics Attitudes-Outcomes Model". That is, students' perceptions of the difficulty of statistics significantly predicted their cognitive competence. These findings were also in line with Sorge and Schau's (2002) study that they reported statistically significant, positive, and large direct effect of difficulty on cognitive competence for undergraduate engineering students (n = 264). Similarly, students' perception of the difficulty of statistics was a statistically significant predictor of interest. Taken together, since Eccles' Model (Wigfield & Eccles, 2000) proposes that individuals' "perception of task demands" influence their "interest-enjoyment value", their "self-concept of abilities" and "expectancies for success", it is possible to state that these findings supported Eccles' Model. However, as stated earlier, the interesting point is that the direct effect from difficulty on cognitive competence was positive when the direct effect from difficulty on interest was negative. These results supported Emmioglu et al. (2010) that they reported positive relationship between cognitive competence and difficulty but negative relationship between interest and difficulty by collecting data from graduate students from education disciplines (n = 54). That is, students' were interested in statistics less when they thought that statistics is an easy subject; however, students' cognitive competence got higher when they thought that statistics is an easy subject. Therefore, the total effect of difficulty on interest was invisible.

5.2. Implications for Further Research

The current study was undertaken with undergraduate and graduate students enrolled in different sections of statistics courses in a highly prestigious, English medium university in Turkey. Therefore, the results of the study were generalized to the target population of the study, which is all the undergraduate and graduate students enrolled in statistics courses in the university that the study was conducted. It is suggested that further studies should examine these relationships in a nation-wide context; so that, the hypothesized relationships can be further generalized by extending current study to the different student populations in Turkey. In addition, it is suggested that further studies should conduct cross-cultural comparisons in which the data are collected from international populations. By this way, it would be possible to examine the hypothesized relationships of the current study with regard to their variation and stability in different cultural contexts.

In the current study, mathematics achievement variable was measured by obtaining students' self-reports of their past and overall mathematics achievement. The results revealed an important finding that self-reports of mathematics achievement did not have any statistically significant direct effect on students' cognitive competence in statistics and on affect toward statistics but on statistics outcomes. The current study suggests further studies to use direct measures, such as mathematics achievement tests, for assessing students' mathematics achievement. In addition, in the current study, two of the indicators of statistics outcomes (students' willingness to use statistics in the remainder of their degree program and their willingness to use statistics when employed) were also measured by students' self-reports. Accordingly, it is also suggested that further studies should utilize direct measures of students' future statistics use such as counting the number of statistics courses taken in the remainder of students' degree program.

In the current study, all of the variables but students' statistics grades after taking statistics courses were measured at a single point in time. Therefore, the proposed relationships were static rather than longitudinal. It is suggested that further research should expand on the current study by using a longitudinal design in which the data are collected prior to, during, and after taking statistics courses. For example, Eccles and her colleagues (Eccles & Wigfield, 2002; Wigfield & Eccles, 2000; 2002) suggested that individuals' performances and achievement choices influence their previous achievement-related experiences across time. It is suggested that their proposal should be tested in a further study by extending the findings of the current study.

The current study hypothesized and tested a hierarchical (recursive) model in which the hierarchical relationships were investigated without any reciprocal paths or feedback loops. It is suggested that further studies should expand the findings of the current study by testing non-recursive models for examining reciprocal relationships among variables.

Existing literature review demonstrated that most of the structural equation modeling studies adapted statistics achievement as an outcome variable (Bude´ et al., 2007; Lalonde & Gardner, 1993; Nasser, 2004; Sorge, 2001). However, students' attitudes are also seen important for students' statistical behavior after they leave the classroom and students' choice of enrolling in a new statistics course (Gal, Ginsburg, & Schau, 1997). Therefore, in the current study, the outcome variable of the hypothesized model included students' willingness to use statistics in the remainder of their degree program and their willingness to use statistics when employed as well as their statistics grades after taking statistics courses. It is suggested that further research can expand the current study by adapting alternative outcome variable(s) such as enrollment in a future statistics courses.

The variables included in the current study explained a statistically significant amount of variance (66%) in statistics outcomes; however, there may be other alternative variables such as students' demographic characteristics (such as gender and age) and personality traits (such as perfectionism) that are important factors for explaining statistics outcomes (Onwuegbuzie & Daley, 1999; Tempelaar, Rienties, Loeff, & Giesbers, 2010). Although, the current study revealed that the hypothesized "Statistics Attitudes-Outcomes Model" fitted to the data well, it does not mean that this model is the best possible model. It is suggested that further research should investigate alternative models.

The hypothesized and tested “Statistics Attitudes-Outcomes Model” of the current study was based on Eccles and her colleagues’ application of expectancy value theory to mathematics education (Eccles & Wigfield, 1995, 2002; Wigfield & Eccles, 2000). The current study showed that the adaptation of Eccles’ Model to the statistics education context was well explained by the data. Further studies could expand on the present findings by adapting “Statistics Attitudes-Outcomes Model” to different subject domains.

5.3. Implications for the Practice of Statistics Education

Educational scientists categorized learning into cognitive, affective, and psychomotor domains. In the field of curriculum and instruction, cognitive domain has gained the most attention. The current study showed that students’ self-reported mathematics achievement and attitudes toward statistics are important for explaining their statistics grades at the end of taking statistics courses and for explaining their willingness to use statistics in the future. That is, this study demonstrated that affective domain is important for explaining students’ statistics outcomes. Therefore, this study suggests that students’ attitudes should be given high priority when designing and implementing statistics curricula. It is highly important to suggest that students’ positive attitudes toward statistics should be among the main goals of the statistics education; and accordingly, a statistics curriculum should involve various instructional practices, which enhance students’ positive attitudes toward statistics. It is also suggested that the effectiveness of statistics curriculum should be evaluated by assessing students’ attitudes toward statistics as well as by assessing short term and long-term outcomes. Accordingly, it is suggested that statistics instructors in universities should be informed and trained about the importance of their students’ attitudes and how to implement and evaluate the instruction in a way to enhance students’ positive attitudes.

Statistics is an important tool for any individual who adapt himself/herself to the ever-changing world in which numerical data are increasingly presented (Ben-Zvi & Garfield, 2010). For this reason, especially in higher education, students from a broad spectrum of disciplines take statistics courses. However, there has been little attempt to attract students to statistics for many years (Gal & Ginsburg, 1994; Snee, 1993). Results of the present study showed that the students' attitudes toward the value of statistics and their interest in statistics had the highest contribution for explaining statistics outcomes. The present study also revealed that students' cognitive competence in statistics and their affect toward statistics had the second highest contribution for explaining statistics outcomes. Accordingly, it is suggested statistics teachers adopt appropriate instructional methods such as value-reappraisal methods (Acee & Weinstein, 2010) to enhance students' awareness about the importance of statistics both in professional and daily life; and therefore, help to increase students' appreciation and valuing of statistics. It is also suggested for statistics teachers to employ statistics activities that are interesting, enjoyable and fun for students to participate which would help students to have more interest and positive affect toward statistics (Berk & Nanda, 1998; Lesser & Pearl, 2008; Milburn, 2007). It is suggested statistics teachers to be aware of their students' perceptions about their capabilities in statistics and deliver the instruction appropriately to the level of students. In addition, revealing the importance of attitudes toward statistics, current study suggests that students' attitudes toward statistics are as necessary as students' achievement in statistics. For this reason, it is recommended statistics teachers to assess their students' attitudes toward statistics for evaluating the effectiveness of their statistics instruction in terms of fostering students' positive attitudes.

The current study also revealed that self-reported mathematics achievement had a role for explaining statistics outcomes. It is suggested statistics teachers to consider the differences in students' mathematics achievement levels and adapt the instruction accordingly.

Overall, the current study demonstrated that students' attitudes toward statistics played an important role for explaining students' statistics outcomes. Several studies suggested that instructional interventions such as technology use (Suanpang et al., 2004; Wiberg, 2009) increased students' positive attitudes toward statistics. Therefore, in sum, it is suggested statistics teachers to adopt appropriate instructional methods to increase positive attitudes toward statistics.

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APPENDIX A

TURKISH VERSION OF THE SURVEY OF ATTITUDES TOWARD STATISTICS-36©

Sevgili Öğrenciler,

İki kısımdan oluşan bu anket istatistiğe yönelik tutumlarınızı belirlemek amacıyla hazırlanmıştır. Ankete verdiğiniz yanıtlar tamamen gizli tutulacak ve hiç bir şekilde açıklanmayacaktır. Anketin ilk kısmında yer alan ifadelere ne kadar katıldığınızı "Kesinlikle Katılmıyorum için 1", "Ne katılmıyorum/Ne katılıyorum için 4", "Kesinlikle Katılıyorum için 7" ile belirtilmiş olan çizelgede ilgili rakamları yuvarlak içine alarak belirtiniz. Yanıtınız bu üç durum dışında ise sizi en iyi tanımladığını düşündüğünüz rakamı yuvarlak içine alarak belirtiniz. Anketin ikinci kısmında ise yine aynı şekilde yanıtınızı ifade eden rakamı yuvarlak içine alarak ya da yanıtınızı ilgili boşluğa yazarak belirtiniz. Soruları boş bırakmamaya ve sadece tek bir seçenek işaretlemeye özen gösteriniz. Katıldığınız için çok teşekkür ederiz.

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Yrd. Doç. Dr. Yeşim Çapa Aydın, capa@metu.edu.tr
Arş. Gör. Esma Emmioğlu, emmioglu@metu.edu.tr

BÖLÜM I

		Kesinlikle Katılmıyorum		Ne Katılmıyorum/Ne Katılıyorum			Kesinlikle Katılıyorum	
1	İstatistik ödevlerimin hepsini tamamlamaya çalıştım.	①	②	③	④	⑤	⑥	⑦
2	İstatistik dersinde çok çalıştım.	①	②	③	④	⑤	⑥	⑦
3	İstatistiği seviyorum.	①	②	③	④	⑤	⑥	⑦
4	İstatistik problemlerini çözmem gerektiğinde kendimi güvensiz hissediyorum.	①	②	③	④	⑤	⑥	⑦
5	Düşünme biçimimden dolayı istatistiği anlamakta zorluk çekiyorum.	①	②	③	④	⑤	⑥	⑦
6	İstatistik formüllerini anlamak kolaydır.	①	②	③	④	⑤	⑥	⑦
7	İstatistik değersizdir.	①	②	③	④	⑤	⑥	⑦
8	İstatistik karmaşık bir alandır.	①	②	③	④	⑤	⑥	⑦
9	İstatistik mesleki eğitimimin zorunlu bir parçası olmalıdır.	①	②	③	④	⑤	⑥	⑦
10	İstatistiksel beceriler benim iş bulmamı kolaylaştıracaktır.	①	②	③	④	⑤	⑥	⑦
11	Bu istatistik dersinde neler olup bittiğine dair hiçbir fikrim yok.	①	②	③	④	⑤	⑥	⑦
12	Başkalarıyla istatistiksel bilgi alışverişi yapabilmeye ilgi duyuyorum.	①	②	③	④	⑤	⑥	⑦
13	İstatistik tipik bir meslek sahibi için gerekli değildir.	①	②	③	④	⑤	⑥	⑦
14	Bütün istatistik sınavlarına çok çalıştım.	①	②	③	④	⑤	⑥	⑦
15	Sınıfta istatistik testlerini yaparken yılgınlık hissediyorum.	①	②	③	④	⑤	⑥	⑦
16	İstatistiksel düşünmek iş dışındaki hayatım için geçerli değildir.	①	②	③	④	⑤	⑥	⑦
17	İstatistiği günlük yaşantımda kullanırım.	①	②	③	④	⑤	⑥	⑦
18	İstatistik dersi boyunca stres altındayım.	①	②	③	④	⑤	⑥	⑦
19	İstatistik dersini almaktan keyif alıyorum.	①	②	③	④	⑤	⑥	⑦
20	İstatistiği kullanmakla ilgileniyorum.	①	②	③	④	⑤	⑥	⑦
21	İstatistiksel sonuçlar günlük yasamda nadiren ortaya çıkar.	①	②	③	④	⑤	⑥	⑦
22	İstatistik birçok kişi tarafından hızlı öğrenilebilinen bir konudur.	①	②	③	④	⑤	⑥	⑦
23	İstatistiksel bilgileri anlamakla ilgileniyorum.	①	②	③	④	⑤	⑥	⑦
24	İstatistik öğrenmek büyük ölçüde disiplin gerektirir.	①	②	③	④	⑤	⑥	⑦
25	İstatistiğin meslek hayatımda uygulaması yoktur.	①	②	③	④	⑤	⑥	⑦
26	İstatistik dersinde birçok matematik hatası yapıyorum.	①	②	③	④	⑤	⑥	⑦
27	Bütün istatistik derslerine katılmaya çalıştım.	①	②	③	④	⑤	⑥	⑦

BÖLÜM I devamı

		Kesinlikle Katılmıyorum		Ne Katılmıyorum/Ne Katılıyorum			Kesinlikle Katılıyorum	
28	İstatistik beni korkutur.	①	②	③	④	⑤	⑥	⑦
29	İstatistiği öğrenmekle ilgileniyorum.	①	②	③	④	⑤	⑥	⑦
30	İstatistik karmaşık hesaplamalar içerir.	①	②	③	④	⑤	⑥	⑦
31	İstatistiği öğrenebilirim.	①	②	③	④	⑤	⑥	⑦
32	İstatistik denklemlerini anlıyorum.	①	②	③	④	⑤	⑥	⑦
33	İstatistiğin hayatımla bir ilgisi yoktur.	①	②	③	④	⑤	⑥	⑦
34	İstatistik çok tekniktir.	①	②	③	④	⑤	⑥	⑦
35	İstatistik kavramlarını anlamak bana zor geliyor.	①	②	③	④	⑤	⑥	⑦
36	Birçok insan istatistiği öğrenmek için yeni bir düşünce tarzı öğrenmek zorundadır	①	②	③	④	⑤	⑥	⑦

BÖLÜM II. Ek Sorular

1. Öğrenci numaranız *	:								
2. Genel Akademik Ortalamanız	:								
3. Şu ana kadar lisede aldığınız matematik dersi sayısı	:								
4. Şu ana kadar üniversitede aldığınız matematik dersi sayısı	:								
5. Şu ana kadar üniversitede aldığınız istatistik dersi sayısı (bu dönem dışında)	:								
6. İstatistik ders saatleri dışında, bir haftada istatistik çalışmaya yaklaşık olarak kaç saat harcıyorsunuz?	:								
7. Bölüm/Alan	○ Eğitim	○ Sosyoloji	○ İşletme	○ Mühendislik					
	○ Psikoloji	○ İktisat	○ Matematik	○ Diğer (lütfen belirtiniz)					
8. Sınıf	1.sınıf ○	2. sınıf ○	3. sınıf ○	4. sınıf ○	Yüksek Lisans ○	Doktora ○	Diğer ○		
9. Geçmişte aldığınız matematik derslerinizde ne ölçüde başarılıydınız?	Çok başarısızdım						Çok başarılıydım		
	①	②	③	④	⑤	⑥	⑦		
10. Matematikte ne kadar başarılısınız?	Çok başarısızım						Çok başarılıyım		
	①	②	③	④	⑤	⑥	⑦		
11. Mezun olup iş hayatınıza başladığınızda istatistiği ne kadar kullanacaksınız?	Hiç kullanmayacağım						Büyük ölçüde kullanacağım		
	①	②	③	④	⑤	⑥	⑦		
12. İstatistik dersinde islenen konuları başardığınıza ne ölçüde güveniyorsunuz?	Hiç güvenmiyorum						Çok güveniyorum		
	①	②	③	④	⑤	⑥	⑦		
13. Bu derste işlenen konuların sizin için zorluk derecesi nedir?	Çok kolay						Çok zor		
	①	②	③	④	⑤	⑥	⑦		
14. Okulunuzu bitirene kadar istatistiği ne ölçüde kullanacaksınız?	Hiç kullanmayacağım						Büyük ölçüde kullanacağım		
	①	②	③	④	⑤	⑥	⑦		
15. Seçim sansınız olsa başka bir istatistik dersini seçme olasılığınız nasıl olurdu?	Asla seçmem						Kesinlikle seçerim		
	①	②	③	④	⑤	⑥	⑦		
16. Geçen hafta süresince genel stres düzeyiniz nasıldı?	Çok az						Çok fazla		
	①	②	③	④	⑤	⑥	⑦		
17. Bu dersten alacağınız notu tam olarak biliyor musunuz?	○ Evet	○ Hayır							
18. Bu dersin sonunda hangi notu almayı bekliyorsunuz?	90-100 ○	85-89 ○	80-84 ○	75-79 ○	70-74 ○	65-69 ○	60-64 ○	50-59 ○	49 ve altı ○

*Bu bilgi ders notunuzu öğrenebilmemiz için gereklidir. Kesinlikle başkalarıyla paylaşılmayacaktır.

Çalışmamıza katıldığınız için teşekkür ederiz.

APPENDIX B

MISSING VALUE ANALYSIS

Syntax:

GET FILE='E:\yeni\tez\dissertation data\son_10_09.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.
MVA grade gpa ach_math Pmatnew A1 A2 A3 C1 C2 C3 V1 V2 V3 D1 D2 D3 I1 E3 I2 I3 E1 E2 employ_use univ_use/DPATTERN/EM TOLERANCE=0.001 CONVERGENCE=0.0001 ITERATIONS=25) .

Selected output:

Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes[a]	
				Count	Percent	Low	High
grade	214	4.8645	1.96814	33	13.4	0	0
ach_math	242	5.5620	1.06153	5	2.0	6	0
Pmatnew	245	3.5959	.60393	2	.8	2	0
C2	247	5.2955	1.26784	0	.0	4	0
C3	247	5.1802	1.26593	0	.0	5	0
V1	247	5.0904	1.05223	0	.0	2	0
V2	247	5.0810	1.20550	0	.0	3	0
V3	247	4.8968	1.29267	0	.0	2	0
D1	247	3.4366	1.06423	0	.0	0	3
D2	247	3.3320	1.18043	0	.0	0	2
D3	247	3.7854	1.17931	0	.0	0	2
I1	247	4.1154	1.59262	0	.0	0	0
I2	244	4.2500	1.83446	3	1.2	0	0
I3	247	4.7409	1.73371	0	.0	15	0
E1	246	4.8455	1.53614	1	.4	7	0
E2	245	4.7429	1.67038	2	.8	11	0
E3	247	5.7146	1.27057	0	.0	5	0
A1	247	4.7045	1.59957	0	.0	0	0
A2	247	4.4636	1.49208	0	.0	0	0
A3	247	4.6235	1.56691	0	.0	0	0
C1	247	5.2632	1.23449	0	.0	3	0
employ_use	244	4.6107	1.55557	3	1.2	10	0
univ_use	242	4.6983	1.63339	5	2.0	11	0

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

EM Means[a]

grade	gpa	ach_math	Pmatnew	A1	A2	A3	C1	C2	C3	V1	V2	V3	D1	D2	D3	I1	E3	I2	I3	E1	E2	employ_use	univ_use
.86	.90	.56	.59	.70	.46	.62	.26	.29	.18	.09	.08	.89	.43	.33	.78	.11	.71	.25	.74	.83	.73	.61	.690

a. Little's MCAR test: Chi-Square = 303.359, DF = 288, Sig. = .256

APPENDIX C

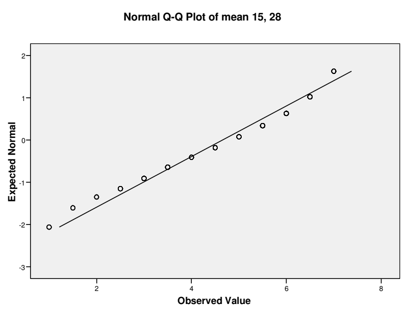
UNIVARIATE AND MULTIVARIATE NORMALITY, MULTIVARIATE OUTLIERS

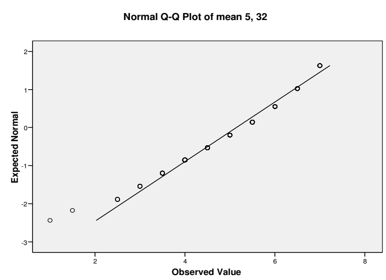
Syntax:

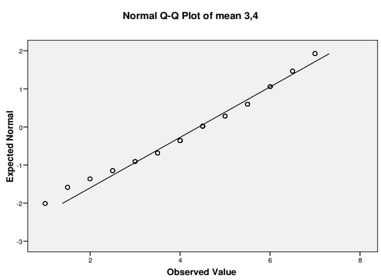
```
DATASET ACTIVATE DataSet1.
EXAMINE
  VARIABLES=A1 A2 A3 C1 C2 C3 V1 V2 V3 D1 D2 D3 I1 I2 I3 E1 E2 E3 Pmatnew
  grade ach_math employ_use univ_use
  /PLOT BOXPLOT NPPLOT
  /COMPARE GROUP
  /STATISTICS DESCRIPTIVES
  /CINTERVAL 95
  /MISSING LISTWISE
  /NOTOTAL.
```

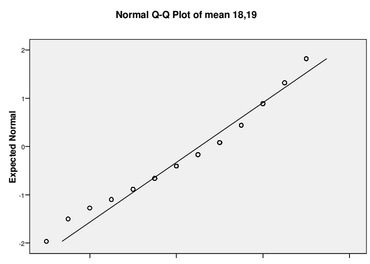
```
include 'C:\Documents and Settings\esma_e\Desktop\normtest.sps'.
normtest vars=A1,A2, A3, C1,C2,C3, expe, V1,V2,V3,D1,D2,D3, E1,E2,
E3,I1,I2,I3,Pmatnew,ach_math,employ_use,univ_use,grade.
```

Selected Output:

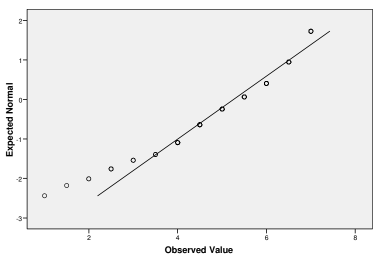




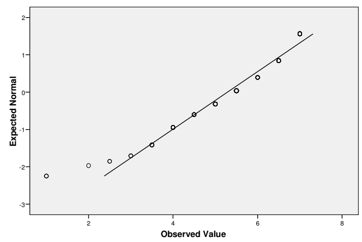




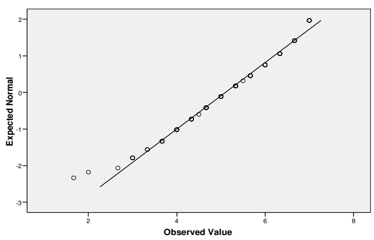
Normal Q-Q Plot of mean 31, 35



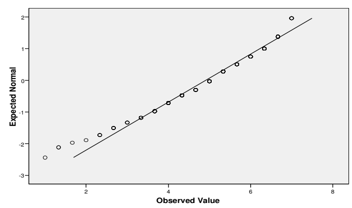
Normal Q-Q Plot of mean 11,26



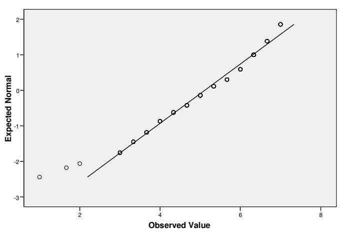
Normal Q-Q Plot of mean 7, 17, 21



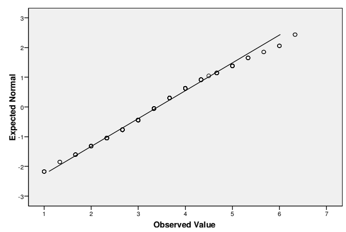
Normal Q-Q Plot of mean 10, 16,33



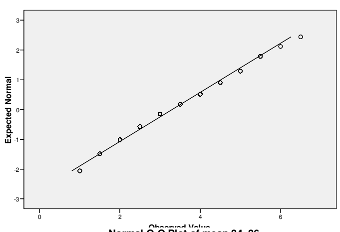
Normal Q-Q Plot of mean 9, 13,25



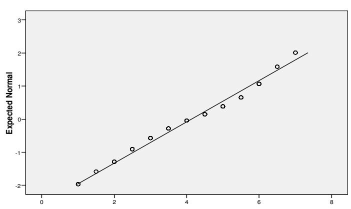
Normal Q-Q Plot of mean 6, 24, 30



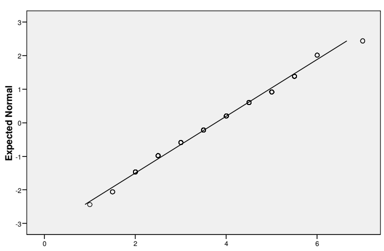
Normal Q-Q Plot of mean 8,22



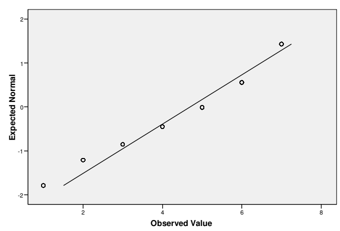
Normal Q-Q Plot of mean 12, 23



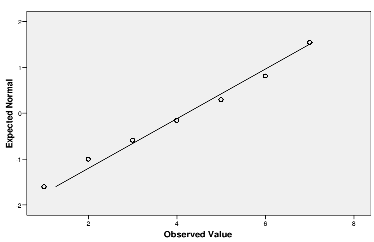
Normal Q-Q Plot of mean 34, 36



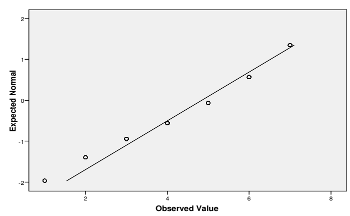
Normal Q-Q Plot of I am interested in learning statistics.



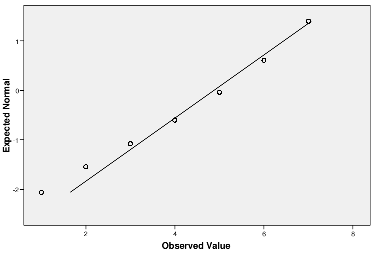
Normal Q-Q Plot of I am interested in using statistics.



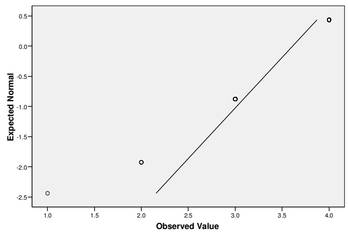
Normal Q-Q Plot of I tried to study hard for every statistics test.



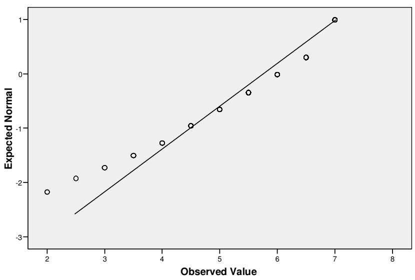
Normal Q-Q Plot of I worked hard in my statistics course



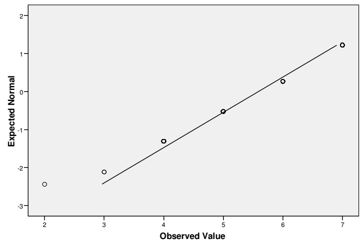
Normal Q-Q Plot of Pmatnew



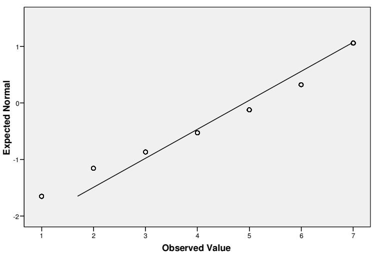
Normal Q-Q Plot of mean 1,27



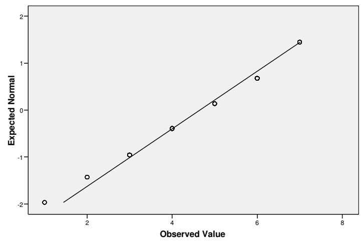
Normal Q-Q Plot of How good at mathematics are you?



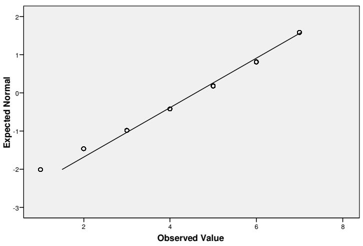
Normal Q-Q Plot of total grade earned after taking statistics course



Normal Q-Q Plot of As you complete the remainder of your degree program, how much will you use statistics?



Normal Q-Q Plot of In the field in which you hope to be employed when you finish school, how much will you use statistics



Measures and tests of skewness:

	g1	sqrt(b1)	z(b1)	p-value
A1	-.4547	-.4512	-2.5792	.0099
A2	-.4096	-.4065	-2.3405	.0193
A3	-.5417	-.5376	-3.0255	.0025
C1	-.8337	-.8274	-4.3802	.0000
C2	-.8751	-.8685	-4.5547	.0000
C3	-.6084	-.6038	-3.3545	.0008
expe	-.4964	-.4926	-2.7955	.0052
V1	-.5102	-.5063	-2.8661	.0042
V2	-.6062	-.6016	-3.3439	.0008
V3	-.5785	-.5741	-3.2084	.0013
D1	.1770	.1756	1.0394	.2986
D2	.2137	.2121	1.2517	.2107
D3	.0955	.0948	.5637	.5729
E1	-.5892	-.5848	-3.2612	.0011
E2	-.6013	-.5968	-3.3202	.0009
E3	-1.0199	-1.0122	-5.1336	0000
I1	-.0951	-.0944	-.5614	.5745
I2	-.2086	-.2070	-1.2220	.2217
I3	-.5770	-.5726	-3.2009	.0014
Pmat	-1.5806	-1.5687	-6.9862	.0000
ach_math	-.5243	-.5203	-2.9379	.0033
employ_u	-.3828	-.3799	-2.1962	.0281
univ_use	-.3464	-.3438	-1.9980	.0457
grade	-.6813	-.6761	-3.7004	.0002

Measures and tests of kurtosis:

	g2	b2-3	z(b2)	p-value
A1	-.7066	-.7190	-3.0680	.0022
A2	-.3834	-.4039	-1.2554	.2093
A3	-.5157	-.5329	-1.8997	.0575
C1	.7382	.6898	1.8422	.0654
C2	.9077	.8550	2.1271	.0334
C3	.0712	.0394	.3573	.7209
expe	-.7329	-.7446	-3.2582	.0011
V1	.4967	.4543	1.3823	.1669
V2	.3395	.3011	1.0410	.2979
V3	.0850	.0529	.3963	.6919
D1	.2425	.2065	.8101	.4179
D2	-.5418	-.5583	-2.0405	.0413
D3	-.4790	-.4970	-1.7096	.0873
E1	-.2381	-.2621	-.6559	.5119
E2	-.4514	-.4701	-1.5728	.1158
E3	.5705	.5263	1.5304	.1259
I1	-.9660	-.9719	-5.4531	.0000
I2	-.9795	-.9851	-5.6188	.0000
I3	-.6493	-.6631	-2.6804	.0074
Pmatnew	2.7971	2.6973	4.1562	.0000
ach_math	.0063	-.0239	.1681	.8665
employ_u	-.3919	-.4122	-1.2936	.1958
univ_use	-.5882	-.6035	-2.3043	.0212
grade	-.6552	-.6689	-2.7187	.0066

Omnibus tests of normality (both chisq, 2 df):

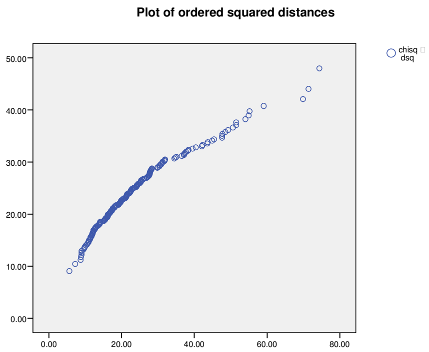
	D'Agostino & Pearson K sq		Jarque & Bera LM test	
	K sq	p-value	LM	p-value
A1	16.0650	.0003	11.0401	.0040
A2	7.0537	.0294	6.8331	.0328
A3	12.7621	.0017	11.9394	.0026
C1	22.5799	.0000	26.6522	.0000
C2	25.2696	.0000	31.0789	.0000
C3	11.3801	.0034	12.1047	.0024
expe	18.4307	.0001	12.6461	.0018
V1	10.1253	.0063	10.2141	.0061
V2	12.2657	.0022	12.7572	.0017
V3	10.4511	.0054	10.9555	.0042
D1	1.7367	.4196	1.3764	.5025
D2	5.7303	.0570	4.0769	.1302
D3	3.2405	.1978	2.3465	.3094

E1	11.0659	.0040	11.9124	.0026
E2	13.4971	.0012	13.6451	.0011
E3	28.6959	.0000	36.2775	.0000
I1	30.0512	.0000	8.1281	.0172
I2	33.0638	.0000	9.4673	.0088
I3	17.4304	.0002	14.5202	.0007
Pmatnew	66.0807	.0000	141.9390	.0000
ach_math	8.6594	.0132	8.9849	.0112
employ_u	6.4969	.0388	6.1952	.0452
univ_use	9.3017	.0096	6.9409	.0311
grade	21.0847	.0000	18.8706	.0001

Multivariate Statistics

Mardia's test

b2p	N(b2p)	p-value
732.9327	21.7494	.0000



Critical values (Bonferroni) for a single multivar. outlier:

critical F(.05/n) =43,27 df = 18, 182
critical F(.01/n) =47,06 df = 18, 182

5 observations with largest Mahalanobis distances:

rank = 1 case# = 199 Mahal D sq = 108,19
rank = 2 case# = 45 Mahal D sq = 48,60
rank = 3 case# = 164 Mahal D sq = 47,42
rank = 4 case# = 19 Mahal D sq = 44,36
rank = 5 case# = 22 Mahal D sq = 43,77

APPENDIX D

ITEM PARCEL CORRELATIONS

	1	2	3	4	5	6	7	8	9	10	11
A1	1										
A2	.65*	1									
A3	.74*	.64*	1	.							
C1	.63*	.60*	.59*	1							
C2	.50*	.44*	.49*	.55*	1						
C3	.57*	.63*	.48*	.70*	.42*	1					
V1	.31*	.29*	.34*	.35*	.25*	.32*	1				
V2	.35*	.32*	.36*	.34*	.32*	.34*	.51*	1			
V3	.31*	.32*	.35*	.37*	.32*	.37*	.67*	.67*	1		
D1	.39*	.29*	.29*	.46*	.24*	.37*	.05	.06	-.01	1	
D2	.48*	.41*	.42*	.45*	.29*	.33*	.13*	.11	.15*	.54*	1
D3	.27*	.17*	.26*	.29*	.27*	.21*	.01	.13*	.02	.37*	.31*
I1	.45*	.52*	.49*	.44*	.27*	.33*	.49*	.46*	.54*	.01	.15*
I2	.47*	.47*	.59*	.47*	.27*	.38*	.54*	.53*	.65*	-.01	.16*
I3	.44*	.53*	.53*	.47*	.29*	.38*	.49*	.45*	.56*	-.03	.14*
E1	.21*	.28*	.24*	.21*	.19*	.15*	.17*	.19*	.21*	-.11	.04
E2	.08	.20*	.18*	.12	.11	.11	.17*	.22*	.19*	-.17*	-.05
E3	.16*	.21*	.27*	.15*	.16*	.14*	.19*	.24*	.23*	-.11	-.09
grade	.24*	.36*	.33*	.29*	.35*	.23*	.14*	.18*	.09	.09	-.01
acmat	.07	.09	.07	.13*	.02	.16*	.04	.12	.05	.13*	-.04
uniuse	.19*	.19*	.21*	.22*	.21*	.20*	.27*	.38*	.43*	-.15*	-.06
emuse	.25*	.27*	.27*	.22*	.20*	.29*	.37*	.58*	.58*	-.02	.02
expe	.21*	.26*	.20*	.19*	.19*	.23*	.02	.08	.01	.10	.06
pmat	.04	.00	.03	.07	-.09	.07	.06	.04	.01	.07	-.03

	13	14	15	16	17	18	19	20	21	22	23	24
D3												
I1	1											
I2	.77*	1										
I3	.75*	.75*	1									
E1	.39*	.38*	.44*	1								
E2	.33*	.38*	.37*	.72*	1							
E3	.35*	.39*	.39*	.52*	.45*	1						
grade	.26*	.28*	.22*	.27*	.23*	.36*	1					
acmat	.07	.04	.06	.05	.05	.02	.18*	1				
uniuse	.43*	.51*	.42*	.37*	.33*	.30*	.20*	.07	1			
emuse	.49*	.52*	.45*	.21*	.28*	.24*	.13	.23*	.60*	1		
expe	.05	.08	.12	.03	.03	.05	.20*	.06	.02	.10	1	
pmat	-.02	.02	-.05	-.04	-.09	-.05	.08	.61*	.04	.09	-.00	1

APPENDIX E

MEASUREMENT MODEL UNSTANDARDIZED RESULTS

Latent variables	*Indicator variables*	*Estimate*	*S.E.*
Math Achievement	Pmat	1	.00
	Achmat	2.60*	1.18
Difficulty	D1	1.00	.00
	D2	1.01*	.11
	D3	.72*	.12
Cognitive Competence	C1	1.00	.00
	C2	.71*	.08
	C3	.89*	.08
	Expe	.49*	.14
Effort	E1	1.00	.00
	E2	.97*	.08
	E3	.56*	.07
Interest	I1	1.00	.00
	I2	1.21*	.06
	I3	1.09*	.06
Affect	A1	1.00	.00
	A2	.87*	.08
	A3	.97*	.07
Value	V1	1.00	.00
	V2	1.17*	.13
	V3	1.54*	.13
Statistics Outcomes	Emuse	1.00	.00
	Uniuse	.90*	.13
	Grade	.36*	.15

*$p<.05$, Note. Expe= Expectancy of Success, Pmat=Previous Math Achievement, Achmat=Overall math achievement, Emuse= willingness to use statistics when employed, Uniuse= willingness to use statistics in the remainder of the degree program

APPENDIX F

STANDARDIZED RESIDUALS FOR COVARIANCES

Standardized Residuals (z-scores) for Covariances/Correlations/Residual Corr

	EXPE	GRADE	PMAT	EMPLUSE	UNIVUSE
EXPE	999.000				
GRADE	2.818	999.000			
PMAT	0.180	0.386	-0.128		
EMPLUSE	0.401	-8.696	0.664	999.000	
UNIVUSE	-0.575	0.185	-0.774	999.000	-1.000
ACHMATH	0.496	2.024	999.000	999.000	-2.294
A1	1.107	2.496	-0.089	-0.604	-0.904
A2	2.588	4.471	-0.951	0.326	-0.473
A3	0.789	3.869	-0.328	-0.055	-0.482
C1	-0.829	3.523	-0.208	-1.842	-0.370
C2	1.118	4.894	-2.523	0.243	0.930
C3	1.704	2.682	-0.368	1.472	-0.011
V1	-1.293	0.057	0.127	-3.668	-2.499
V2	-0.176	0.907	0.278	6.025	-0.158
V3	-1.798	-2.306	-0.691	999.000	-1.637
D1	-0.306	1.577	0.277	0.297	-2.445
D2	-0.881	-0.074	-1.289	1.034	-0.571
D3	-1.010	1.610	0.695	1.447	-0.761
E1	-0.409	3.632	-2.178	-4.477	999.000
E2	-0.254	2.685	-1.704	-0.356	999.000
E3	0.231	4.707	-1.062	0.363	8.089
IN1	-1.219	4.972	-0.598	-0.321	999.000
IN2	-0.820	4.167	0.123	-0.383	999.000
IN3	-0.031	2.810	-1.009	-1.439	-0.602

	ACHMATH	A1	A2	A3	C1
ACHMATH	999.000				
A1	-0.351	0.000			
A2	0.690	-1.832	0.000		
A3	0.011	999.000	-1.238	0.000	
C1	999.000	-0.366	0.095	-1.826	0.000
C2	-1.468	2.216	1.353	3.794	0.091
C3	4.245	999.000	7.975	-2.624	999.000
V1	-0.119	0.316	0.798	1.162	0.758
V2	1.568	1.321	1.214	1.551	0.428
V3	-1.402	-1.432	-0.596	-0.223	-1.782
D1	4.452	-0.221	-2.085	-2.764	0.426

D2	-3.215	999.000	3.004	4.250	2.322
D3	-1.359	0.249	-1.624	0.010	0.068
E1	999.000	-0.839	2.380	0.330	0.567
E2	999.000	-2.523	0.291	-0.273	-0.977
E3	0.081	0.119	1.836	2.127	0.451
IN1	1.439	-1.181	2.058	-0.258	0.275
IN2	-0.601	-1.724	-0.720	3.510	0.646
IN3	0.544	-1.661	4.770	1.209	1.126

	C2	C3	V1	V2	V3
C2	0.000				
C3	-3.201	0.000			
V1	0.437	0.965	0.000		
V2	1.831	1.170	999.000	0.000	
V3	0.696	0.796	999.000	-0.300	0.000
D1	-1.511	-0.590	-0.213	0.027	-2.863
D2	0.176	-0.824	1.418	1.138	2.001
D3	1.433	-1.177	-0.536	1.621	-0.638
E1	0.758	-0.281	-0.042	0.013	-0.754
E2	-0.073	-0.772	0.145	0.896	-0.498
E3	1.051	0.491	1.019	2.119	1.182
IN1	-0.599	-1.201	0.880	-0.622	-2.219
IN2	-0.942	-0.424	1.997	1.137	2.421
IN3	-0.269	0.231	0.877	-0.869	-1.033

	D1	D2	D3	E1	E2
D1	0.000				
D2	999.000	0.000			
D3	-0.229	-0.997	0.000		
E1	-0.323	2.485	-0.842	999.000	
E2	-1.781	0.615	-1.270	999.000	999.000
E3	-1.085	-0.591	-0.158	999.000	-1.547
IN1	-0.944	2.820	-1.135	-0.316	-1.006
IN2	-1.728	2.927	-0.545	-1.368	-0.232
IN3	-1.716	2.211	-2.269	1.645	-0.120

	E3	IN1	IN2	IN3
E3	0.000			
IN1	1.894	0.000		
IN2	2.747	0.207	999.000	
IN3	2.603	999.000	-0.892	0.000

APPENDIX G

STRUCTURAL MODEL UNSTANDARDIZED RESULTS

Structural part	Estimate	S.E.
Cognitive Competence on		
Difficulty	.92*	.12
Math Achievement	.35	.23
Interest on		
Difficulty	-1.08*	.21
Cognitive Competence	.48*	.23
Affect	.75*	.18
Affect on		
Cognitive Competence	1.05*	.11
Math Achievement	-.16	.20
Effort on		
Cognitive Competence	-.17	.10
Interest	.62*	.08
Value on		
Interest	.43*	.06
Affect	-.02	.05
Statistics Outcomes on		
Effort	.19*	.09
Cognitive Competence	-.17	.22
Affect	.09	.17
Value	1.19*	.22
Math Achievement	.79*	.28

*p<.05

APPENDIX H

STANDARDIZED TOTAL INDIRECT, DIRECT, TOTAL EFFECTS MPLUS INPUT AND SELECTED OUTPUT

INPUT:

```
TITLE: structural model
DATA: File is
"C:\Documents and Settings\esma_e\Desktop\tez10eylul.dat";
VARIABLE: NAMES ARE
sec id course courid student grade gpa      mathigh      matuni Pstat hour major
level degree Pmat achmath empluse futuse conf diff univuse choice
stress know expe i1 i2 i3 i4 i5 i6 i7 i8 i9 i10 i11 i12 i13
i14 i15 i16 i17 i18 i19 i20 i21 i22 i23 i24 i25 i26 i27 i28 i29 i30 i31 i32
i33 i34 i35 i36 premat A1 A2 A3 C1 C2 C3 V1 V2 V3 D1 D2 D3 In1
In2 In3 E1 E2 E3 MAH1 Pmatnew;
usevariables are expe grade Pmatnew empluse univuse achmath
A1 A2 A3 C1 C2 C3 V1 V2 V3 D1 D2 D3 E1 E2 E3 In1 In2 In3;
MISSING ARE ALL (999);
ANALYSIS: ESTIMATOR= MLR;
MODEL:
math BY Pmatnew achmath;
diffi BY D1 D2 D3;
cognit BY C1 C2 C3 expe;
effort BY E1 E2 E3;
interest BY In1 In2 In3;
affect BY A1 A2 A3;
value BY V1 V2 V3;
outcome BY empluse univuse grade;
cognit on diffi math;
interest on diffi cognit affect;
affect on cognit math;
effort on cognit interest;
value on interest affect;
outcome on effort cognit affect value math;

MODEL INDIRECT:
affect IND cognit diffi;
interest IND cognit diffi;
interest IND affect cognit diffi;
effort IND cognit interest diffi;
effort IND interest diffi;
effort IND cognit affect interest diffi;
effort IND cognit diffi;
value IND cognit affect interest diffi;
value IND cognit affect diffi;
```

value IND cognit interest diffi;
value IND interest diffi;
outcome IND interest effort diffi;
outcome IND cognit effort diffi;
outcome IND interest value diffi;
outcome IND cognit diffi;
outcome IND cognit interest effort diffi;
outcome IND cognit interest value diffi;
outcome IND cognit affect interest value diffi;
outcome IND cognit affect interest effort diffi;
outcome IND cognit affect diffi;
outcome IND cognit affect value diffi;
affect IND cognit math;
interest IND cognit math;
interest IND affect math;
interest IND cognit affect math;
effort IND cognit math;
effort IND affect interest math;
effort IND cognit interest math;
effort IND cognit affect interest math;
value IND affect math;
value IND affect interest math;
value IND cognit interest math;
value IND cognit affect interest math;
value IND cognit affect math;
outcome IND cognit effort math;
outcome IND cognit interest effort math;
outcome IND cognit interest value math;
outcome IND affect interest value math;
outcome IND affect interest effort math;
outcome IND affect math;
outcome IND cognit math;
outcome IND affect value math;
outcome IND cognit affect math;
outcome IND cognit affect interest value math;
outcome IND cognit affect interest effort math;
outcome IND cognit affect value math;
outcome IND cognit affect interest effort math;
interest IND affect cognit;
effort IND interest cognit;
effort IND affect interest cognit;
value IND interest cognit;
value IND affect interest cognit;
value IND affect cognit;
outcome IND effort cognit;
outcome IND interest effort cognit;
outcome IND interest value cognit;
outcome IND affect interest value cognit;
outcome IND affect interest effort cognit;

```
  outcome IND affect value cognit;
  outcome IND affect cognit;
  effort IND interest affect;
  value IND interest affect;
  outcome IND value affect;
  outcome IND interest effort affect;
  outcome IND interest value affect;
  outcome IND effort interest;
  outcome IND value interest;
  effort IND cognit;
  interest IND diffi;
  interest IND cognit;
  affect IND math;
  value IND affect;
  outcome IND math;
  outcome IND affect;
  outcome IND cognit;
Output: stdyx modindices residual fsdeterminacy;
```

SELECTED OUTPUT:

Effects from MATH to AFFECT				
		Two-Tailed		
	Estimate	S.E	Est./S.E.	P-Value
Total	0.054	0.062	0.879	0.379
Total indirect	0.097	0.060	1.601	0.109
Specific indirect				
AFFECT				
COGNIT				
MATH	0.097	0.060	1.601	0.109
Direct				
AFFECT				
MATH	-0.043	0.053	-0.801	0.423

Effects from DIFFI to INTEREST				
Total	0.046	0.075	0.622	0.534
Total indirect	0.690	0.105	6.545	0.000
Specific indirect				
INTEREST				
COGNIT				
DIFFI	0.261	0.132	1.975	0.048
INTEREST				
AFFECT				
COGNIT				
DIFFI	0.429	0.109	3.938	0.000
Direct				
INTEREST				
DIFFI	-0.643	0.101	-6.377	0.000

Effects from COGNIT to INTEREST				
Total	1.021	0.098	10.447	0.000
Total indirect	0.635	0.149	4.266	0.000
Specific indirect				
INTEREST				
AFFECT				
COGNIT	0.635	0.149	4.266	0.000
Direct				
INTEREST				
COGNIT	0.387	0.187	2.065	0.039

Effects from COGNIT to EFFORT				
Total	0.499	0.094	5.286	0.000
Total indirect	0.635	0.106	5.995	0.000
Specific indirect				
EFFORT				
INTEREST				
COGNIT	0.240	0.123	1.950	0.051
EFFORT				
INTEREST				
AFFECT				
COGNIT	0.395	0.103	3.847	0.000
Direct				
EFFORT				
COGNIT	-0.136	0.079	-1.709	0.087

Effects from AFFECT to VALUE				
Total	0.549	0.131	4.179	0.000
Total indirect	0.575	0.117	4.904	0.000
Specific indirect				
VALUE				
INTEREST				
AFFECT	0.575	0.117	4.904	0.000
Direct				
VALUE				
AFFECT	-0.026	0.083	-0.314	0.754

Effects from MATH to OUTCOME				
Total	0.252	0.080	3.169	0.002
Total indirect	0.040	0.041	0.969	0.333
Specific indirect				
OUTCOME COGNIT MATH	-0.016	0.022	-0.693	0.488
OUTCOME AFFECT MATH	-0.004	0.009	-0.450	0.653
OUTCOME EFFORT COGNIT MATH	-0.003	0.003	-0.940	0.347
OUTCOME AFFECT COGNIT MATH	0.009	0.018	0.506	0.613
OUTCOME VALUE AFFECT MATH	0.001	0.002	0.304	0.761
OUTCOME EFFORT INTEREST COGNIT MATH	0.005	0.005	1.058	0.290
OUTCOME EFFORT INTEREST AFFECT MATH	-0.004	0.006	-0.678	0.498
OUTCOME VALUE INTEREST COGNIT MATH	0.023	0.017	1.345	0.179
OUTCOME VALUE INTEREST AFFECT MATH	-0.017	0.022	-0.768	0.443
OUTCOME VALUE AFFECT COGNIT MATH	-0.002	0.005	-0.314	0.754

OUTCOME				
EFFORT				
INTEREST				
AFFECT				
COGNIT				
MATH	0.009	0.008	1.129	0.259
OUTCOME				
VALUE				
INTEREST				
AFFECT				
COGNIT				
MATH	0.038	0.026	1.446	0.148
Direct				
OUTCOME				
MATH	0.213	0.074	2.892	0.004

Effects from AFFECT to OUTCOME				
Total	0.557	0.215	2.588	0.010
Total indirect	0.463	0.117	3.961	0.000
Specific indirect				
OUTCOME				
VALUE				
AFFECT	-0.018	0.056	-0.315	0.753
OUTCOME				
EFFORT				
INTEREST				
AFFECT	0.091	0.050	1.826	0.068
OUTCOME				
VALUE				
INTEREST				
AFFECT	0.390	0.089	4.357	0.000
Direct				
OUTCOME				
AFFECT	0.094	0.172	0.544	0.586

Effects from COGNIT to OUTCOME				
Total	0.563	0.113	4.992	0.000
Total indirect	0.701	0.152	4.604	0.000
Specific indirect				
OUTCOME				
EFFORT				
COGNIT	-0.027	0.021	-1.271	0.204
OUTCOME				
AFFECT				
COGNIT	0.080	0.148	0.541	0.589
OUTCOME				
EFFORT				
INTEREST				
COGNIT	0.047	0.036	1.309	0.191

OUTCOME VALUE INTEREST COGNIT	0.203	0.111	1.835	0.067
OUTCOME VALUE AFFECT COGNIT	-0.015	0.048	-0.316	0.752
OUTCOME EFFORT INTEREST AFFECT COGNIT	0.078	0.044	1.784	0.074
OUTCOME VALUE INTEREST AFFECT COGNIT	0.334	0.083	4.048	0.000
Direct				
OUTCOME COGNIT	-0.138	0.176	-0.786	0.432

Effects from DIFFI to AFFECT				
Sum of indirect	0.579	0.052	11.108	0.000
Specific indirect				
AFFECT COGNIT DIFFI	0.579	0.052	11.108	0.000

Effects from MATH to AFFECT				
Sum of indirect	0.097	0.060	1.601	0.109
Specific indirect				
AFFECT COGNIT MATH	0.097	0.060	1.601	0.109

Effects from DIFFI to INTEREST				
Sum of indirect	0.690	0.105	6.545	0.000
Specific indirect				
INTEREST COGNIT DIFFI	0.261	0.132	1.975	0.048
INTEREST AFFECT COGNIT DIFFI	0.429	0.109	3.938	0.000

Effects from MATH to INTEREST				
Sum of indirect	0.012	0.048	0.251	0.802
Specific indirect				
INTEREST				
COGNIT				
MATH	0.044	0.031	1.409	0.159
INTEREST				
AFFECT				
MATH	-0.032	0.041	-0.763	0.445
INTEREST				
COGNIT				
AFFECT				
MATH	0.000	0.000	0.000	1.000

Effects from COGNIT to INTEREST				
Sum of indirect	0.635	0.149	4.266	0.000
Specific indirect				
INTEREST				
AFFECT				
COGNIT	0.635	0.149	4.266	0.000

Effects from DIFFI to EFFORT				
Sum of indirect	-0.492	0.115	-4.276	0.000
Specific indirect				
EFFORT				
COGNIT				
INTEREST				
DIFFI	0.000	0.000	0.000	1.000
EFFORT				
INTEREST				
DIFFI	-0.400	0.081	-4.919	0.000
EFFORT				
COGNIT				
AFFECT				
INTEREST				
DIFFI	0.000	0.000	0.000	1.000
EFFORT				
COGNIT				
DIFFI	-0.092	0.055	-1.678	0.093

Effects from MATH to EFFORT				
Sum of indirect	-0.015	0.014	-1.100	0.271
Specific indirect				
EFFORT				
COGNIT				
MATH	-0.015	0.014	-1.100	0.271

EFFORT				
AFFECT				
INTEREST				
MATH	0.000	0.000	0.000	1.000
EFFORT				
COGNIT				
INTEREST				
MATH	0.000	0.000	0.000	1.000
EFFORT				
COGNIT				
AFFECT				
INTEREST				
MATH	0.000	0.000	0.000	1.000

Effects from COGNIT to EFFORT				
Sum of indirect	0.240	0.123	1.950	0.051
Specific indirect				
EFFORT				
INTEREST				
COGNIT	0.240	0.123	1.950	0.051
EFFORT				
AFFECT				
INTEREST				
COGNIT	0.000	0.000	0.000	1.000

Effects from AFFECT to EFFORT				
Sum of indirect	0.460	0.107	4.308	0.000
Specific indirect				
EFFORT				
INTEREST				
AFFECT	0.460	0.107	4.308	0.000

Effects from DIFFI to VALUE				
Sum of indirect	-0.500	0.090	-5.572	0.000
Specific indirect				
VALUE				
COGNIT				
AFFECT				
INTEREST				
DIFFI	0.000	0.000	0.000	1.000
VALUE				
COGNIT				
AFFECT				
DIFFI	0.000	0.000	0.000	1.000
VALUE				
COGNIT				
INTEREST				
DIFFI	0.000	0.000	0.000	1.000

VALUE				
INTEREST				
DIFFI	-0.500	0.090	-5.572	0.000

Effects from MATH to VALUE				
Sum of indirect	0.001	0.004	0.304	0.761
Specific indirect				
VALUE				
AFFECT				
MATH	0.001	0.004	0.304	0.761
VALUE				
AFFECT				
INTEREST				
MATH	0.000	0.000	0.000	1.000
VALUE				
COGNIT				
INTEREST				
MATH	0.000	0.000	0.000	1.000
VALUE				
COGNIT				
AFFECT				
INTEREST				
MATH	0.000	0.000	0.000	1.000
VALUE				
COGNIT				
AFFECT				
MATH	0.000	0.000	0.000	1.000

Effects from COGNIT to VALUE				
Sum of indirect	0.278	0.150	1.854	0.064
Specific indirect				
VALUE				
INTEREST				
COGNIT	0.300	0.155	1.941	0.052
VALUE				
AFFECT				
INTEREST				
COGNIT	0.000	0.000	0.000	1.000
VALUE				
AFFECT				
COGNIT	-0.022	0.071	-0.315	0.753

Effects from AFFECT to VALUE				
Sum of indirect	0.575	0.117	4.904	0.000
Specific indirect				
VALUE				
INTEREST				
AFFECT	0.575	0.117	4.904	0.000

Effects from DIFFI to OUTCOME				
Sum of indirect	-0.093	0.119	-0.783	0.434
Specific indirect				
OUTCOME				
INTEREST				
EFFORT				
DIFFI	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
EFFORT				
DIFFI	0.000	0.000	0.000	1.000
OUTCOME				
INTEREST				
VALUE				
DIFFI	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
DIFFI	-0.093	0.119	-0.783	0.434
OUTCOME				
COGNIT				
INTEREST				
EFFORT				
DIFFI	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
INTEREST				
VALUE				
DIFFI	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
AFFECT				
INTEREST				
VALUE				
DIFFI	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
AFFECT				
INTEREST				
EFFORT				
DIFFI	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
AFFECT				
DIFFI	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
AFFECT				
VALUE				
DIFFI	0.000	0.000	0.000	1.000

Effects from MATH to OUTCOME				
Sum of indirect	-0.020	0.030	-0.660	0.509
Specific indirect				
OUTCOME				
COGNIT				
EFFORT				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
INTEREST				
EFFORT				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
INTEREST				
VALUE				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
AFFECT				
INTEREST				
VALUE				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
AFFECT				
INTEREST				
EFFORT				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
AFFECT				
MATH	-0.004	0.009	-0.450	0.653
OUTCOME				
COGNIT				
MATH	-0.016	0.022	-0.693	0.488
OUTCOME				
AFFECT				
VALUE				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
AFFECT				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
AFFECT				
INTEREST				
VALUE				
MATH	0.000	0.000	0.000	1.000

OUTCOME				
COGNIT				
AFFECT				
INTEREST				
EFFORT				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
AFFECT				
VALUE				
MATH	0.000	0.000	0.000	1.000
OUTCOME				
COGNIT				
AFFECT				
INTEREST				
EFFORT				
MATH	0.000	0.000	0.000	1.000

Effects from COGNIT to OUTCOME				
Sum of indirect	0.053	0.154	0.346	0.729
Specific indirect				
OUTCOME				
EFFORT				
COGNIT	-0.027	0.021	-1.271	0.204
OUTCOME				
INTEREST				
EFFORT				
COGNIT	0.000	0.000	0.000	1.000
OUTCOME				
INTEREST				
VALUE				
COGNIT	0.000	0.000	0.000	1.000
OUTCOME				
AFFECT				
INTEREST				
VALUE				
COGNIT	0.000	0.000	0.000	1.000
OUTCOME				
AFFECT				
INTEREST				
EFFORT				
COGNIT	0.000	0.000	0.000	1.000
OUTCOME				
AFFECT				
VALUE				
COGNIT	0.000	0.000	0.000	1.000

OUTCOME				
AFFECT				
COGNIT	0.080	0.148	0.541	0.589

Effects from AFFECT to OUTCOME				
Sum of indirect	-0.018	0.056	-0.315	0.753
Specific indirect				
OUTCOME				
VALUE				
AFFECT	-0.018	0.056	-0.315	0.753
OUTCOME				
INTEREST				
EFFORT				
AFFECT	0.000	0.000	0.000	1.000
OUTCOME				
INTEREST				
VALUE				
AFFECT	0.000	0.000	0.000	1.000

Effects from INTEREST to OUTCOME				
Sum of indirect	0.649	0.091	7.140	0.000
Specific indirect				
OUTCOME				
EFFORT				
INTEREST	0.123	0.065	1.894	0.058
OUTCOME				
VALUE				
INTEREST	0.526	0.083	6.336	0.000

APPENDIX I

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APPENDIX J

TURKISH SUMMARY

TÜRKÇE ÖZET

MATEMATİK BAŞARISI, İSTATİSTİĞE YÖNELİK TUTUMLAR VE İSTATİSTİK KAZANIMLARI ARASINDAKİ İLİŞKİLERİ İNCELEYEN YAPISAL EŞİTLİK MODELİ

GİRİŞ

İstatistik, günlük yaşantımızda sıklıkla karşımıza çıkan "veriler yoluyla öğrenme bilimi" olarak tanımlanmaktadır (Moore, 2005, p.206). İnternet, gazete, televizyon, reklam afişleri gibi yollarla her gün çok sayıda istatistiksel bilgi sunulmaktadır. Bu nedenle istatistiği anlamak günümüz insanları için vazgeçilmez bir gereklilik haline gelmiştir. Hand'ın (1998) de belirttiği üzere istatistik gerçek yaşam problemlerini çözmekle ilgilenir. Öte yandan istatistik, uzun yıllar boyunca matematiğin bir parçası olarak görülmüş (Greer, 2000) ve buna bağlı olarak "istatistiği anlamak sınırlı bir azınlığın becerisi olarak kalmıştır" (Lajoie, Jacobs, & Lavigne, 1995, p.401).

İstatistik eğitiminin tarihine bakıldığında, öğrencilerin istatistik dersleriyle[1] 20. yüzyılın başından beri tanışmış olduğu bilinmektedir (Verhoeven, 2009). İstatistik derslerinin temelleri, 1925 yılında R.A. Fisher tarafından yazılan "Araştırmacılar için İstatistik Yöntemleri" kitabına dayanmaktadır. İstatistik derslerinin ilk uygulamalarında, öğretim geleneksel bir yaklaşımla ele alınmış, derslerde olasılık teorisi ve belirli istatistiksel ve matematiksel işlemler üzerinde yoğunlaşılmıştır. Öğrencilerden istatistiksel bilgileri ezberlemeleri ve

[1] Bu çalışmada, istatistik dersleri ile lisans ve lisansüstü eğitim alan, istatistik alanı dışındaki öğrencilere verilen servis derslerini ifade etmektedir.

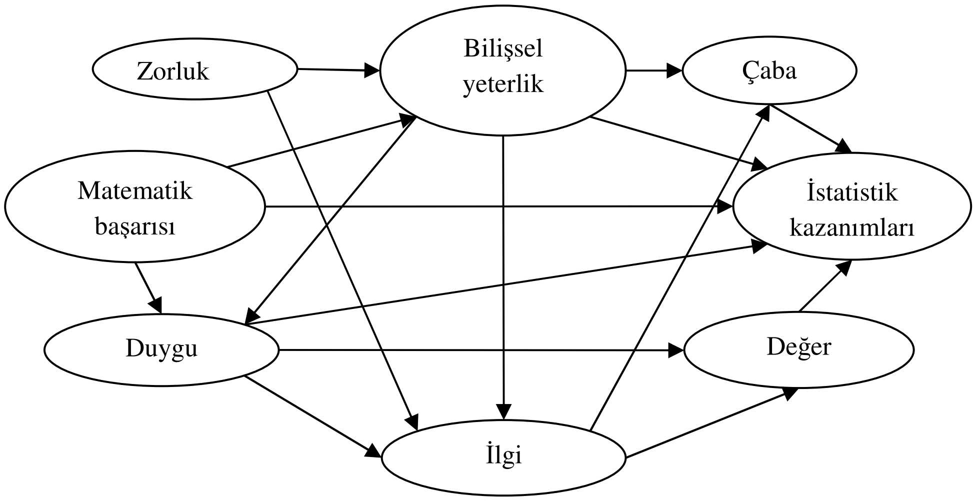
belirli standartlar içinde kuralları takip etmeleri beklenmiştir (Vanhoof, 2010). 90'lı yıllara gelindiğinde ise istatistik öğretimine bilgisayarların girmesiyle bir devrim yaşanmıştır (Hand, 1998). İstatistik paket programları derslerdeki matematik önceliğinin azalmasını ve istatistiksel uygulamalara yer verilmesini sağlamıştır. Günümüzde, teknolojinin istatistik derslerine daha fazla dahil olmasıyla veri analizi ve simülasyonlar derslerde artarak kullanılmaktadır. Buna bağlı olarak istatistik eğitiminin amacı matematiksel işlemler yerine istatistik kavramlarını öğrenmeye doğru yönelmiştir (American Statistical Association, 2010). Bugün istatistik dersleri Sosyal ve Fen alanlarında eğitim alan geniş bir öğrenci kitlesi için zorunlu bir derstir. Oysaki, bu ölçüde yaygın bir ders olmasına rağmen, istatistik eğitimi üzerine yapılan araştırma sayısı oldukça kısıtlıdır. İstatistik eğitimi üzerine bilimsel makalelerin yayınlandığı ilk bilimsel dergi (Statistics Education Research Journal, SERJ) ancak 2002 yılında yayın hayatına başlamıştır (Garfield & Ben-Zvi, 2007; Ottaviani, 2005). Bu tarihten itibaren istatistik eğitimi araştırmalarında hızlı bir artış olmuştur (Shaughnessy, 2007).

İstatistik eğitimi üzerine yapılan araştırmaların büyük bir kısmında istatistik öğretiminin bilişsel boyutları üzerinde durulmuş, duyuşsal alan ise daha az ilgi görmüştür (Gal & Ginsburg, 1994; Shaughnessy, 2007). Bilişsel alan üzerine odaklanan çalışmalar özellikle öğrencilerin istatistik başarısı, istatistiksel düşünmeleri, muhakemeleri (statistical reasoning), ve istatistik okur-yazarlığı kazanımları üzerine olmuştur (Gal, 2002; Garfield & Gal, 1999; Groth, 2006; Lavigne & Lajoie, 2007; Mooney, 2002; Rumsey, 2002; Tempelaar, Gijselaers, & Schim van der Loeff, 2006). Bu çalışmalardan bazılarında matematik başarısının istatistik başarısına katkı sağladığını belirtmiştir (Galli, Matteo, Chiesi, & Primi, 2008; Johnson & Kuennen, 2006; Lalonde & Gardner, 1993; Nasser, 2004; Wisenbaker, Scott, & Nasser, 2000).

Öğrencilerin istatistik derslerindeki bilişsel kazanımları üzerine odaklanan çalışmaların yanı sıra, kısıtlı sayıdaki bazı çalışmalarda da öğrencilerin istatistiğe yönelik tutumları üzerinde durulmuştur. Bu çalışmaların çoğunda tarama deseni kullanılmış ve istatistiğe yönelik olumlu tutumların istatistik dersindeki başarıyı artırdığı rapor edilmiştir (Chiesi & Primi, 2008; Dempster & McCorry, 2009; Evans, 2007; Limpscomb, Hotard, Shelley, & Baldwin, 2002; Sizemore & Lewandowski, 2009; Sorge & Schau, 2002; Tempelaar et al., 2007). Araştırmacılar ayrıca, istatistiğe yönelik olumlu tutum geliştirmenin öğrencilerin istatistik dersi alma seçimleri gibi ileriye yönelik davranışlarına da etkisi olduğunu savunmaktadır (Garfield, Hogg, Schau, & Whittinghill, 2002; Schau, 2003).

Çalışmanın Amacı

Bu çalışmanın amacı matematik başarısı, istatistiğe yönelik tutumlar, ve istatistik kazanımları arasındaki yapısal ilişkilerin Yapısal Eşitlik Modellemesi ile test edilerek incelenmesidir. Çalışmada hipotez edilen İstatistik Tutum-Kazanım Modeli (Statistics Attitudes-Outcomes Model), Eccles ve arkadaşlarının geliştirdikleri beklenti-değer modeli (Eccles, 1983; Eccles & Wigfield, 1995) ve İstatistik Tutum-Başarı Yapısal Modeline (Sorge & Schau, 2002) dayanmaktadır. Çalışmada, hipotez edilen modelin genel yapısının test edilmesinin yanı sıra değişkenler arasındaki doğrudan ve dolaylı ilişkiler de test edilmiştir. Çalışmanın kavramsal modeli Şekil 1'de gösterilmiştir.



Şekil 1 Çalışmanın Kavramsal Modeli

Çalışmanın Önemi

İstatistik derslerini alan öğrencilerden, istatistiksel becerilere sahip olmaları ve istatistiği kullanmaya yönelik olarak güdülenmeleri beklenmektedir. Fakat bu beklentilerin çoğu zaman karşılanamadığı ve istatistiğin öğrenciler arasında olumsuz bir üne sahip olduğu bilinmektedir (Onwuegbuzie & Wilson, 2003; Snee, 1993). Bu nedenle, istatistik derslerinin öğrenciler için ilgi çekici hale getirilmesi ve öğrencilerin istatistiği öğrenmeye güdülenecek şekilde derslerin yeniden düzenlenmesi önerilmektedir (Carnell, 2008; Dempster & McCorry, 2009; Murtonen & Lehtinen, 2003; Wiberg, 2009). Buna bağlı olarak, öğrencilerin istatistiğe yönelik tutumlarını anlamak ve bu şekilde onların olumlu tutumlar geliştirmelerine yardımcı olmak büyük önem taşımaktadır. Öğrencilerin istatistiğe yönelik tutumlarını anlamaya yönelik bazı çalışmalar yapılmış olmakla birlikte bu çalışmaların pek çoğuyla ilgili bazı sınırlılıklar mevcuttur. Öncelikle, bu çalışmaların çoğu eğitim kuramlarına dayanmak yerine araştırmacıların tecrübelerine dayanmaktadır (örneğin, Bartsch, 2006; Evans, 2007; Rhoads & Hubele, 2000; Wiberg, 2009). Ayrıca, bu çalışmalarda kullanılan ölçekler arasında tutarsızlıklar görülmekte ve kullanılan ölçeklerin pek çoğu sıklıkla eleştirilmektedir (Rhoads & Hubele, 2000; Schau, Stevens, Dauphinee, & Del Vecchio, 1995; Waters, Martelli, Zakrajsek, & Popovich, 1988). Bu çalışmalarla ilgili bir sınırlılık da çalışmaların büyük bir kısmının istatistiğe yönelik tutum ve istatistik başarısı arasındaki ilişkilerin bir bölümünü incelemesidir (örneğin, Dempster & McCorry, 2009; Lawless & Kulikowich, 2006).

Bu çalışmanın sonuçları, mevcut alanyazına ve istatistik eğitimi uygulamalarına katkı sağlamak adına birçok açıdan değer taşımaktadır. Öncelikle, çalışmada hipotez edilen ve test edilen İstatistik Tutum-Kazanım Modeli, Eccles' ve arkadaşlarının geliştirdiği beklenti-değer modeli (Eccles, 1983, 2005; Eccles & Wigfield, 2002) başta olmak üzere sağlam kuramsal temellere dayanmaktadır. Bunun yanı sıra, çalışmada güncel, geçerlik-güvenirlik çalışmaları geniş ölçüde rapor edilmiş ve kuramsal temellere dayanan İstatistiğe yönelik Tutum Ölçeği© uygulanmıştır. Ayrıca, çalışmanın bağımlı (outcome) değişkeni olan istatistik kazanımları, öğrencilerin istatistik başarılarının yanı sıra ilerde istatistiği kullanma isteklerini de içermektedir. Bu özelliği ile bu çalışma alan yazına özgün bir katkı sağlamaktadır. Bilindiği kadarıyla alan yazında böyle bir çalışma mevcut değildir. Oysaki öğrencilerin istatistiğe yönelik tutumlarının öğrencilerin istatistik derslerini aldıktan sonraki davranışlarını etkilediği öngörülmektedir (Gal, Ginsburg, & Schau, 1997).

Çalışmada kullanılan İstatistiğe yönelik Tutum Ölçeği© Türkçeye uyarlanarak ülkemiz alan yazınına kazandırılmıştır. Türkiye'de yapılan çalışmaların azlığı göz önünde bulundurulduğunda bu çalışmanın ülkemiz alan yazınına katkı sağlayacağı düşünülmektedir. Diğer bir yandan Türkiye ile diğer ülkeleri karşılaştırmak açısından, kültürler arası karşılaştırma çalışmaları için de bu çalışmanın faydalı olacağı düşünülmektedir.

Son olarak, istatistik nicel araştırmalar için vazgeçilmez bir araçtır; dolayısıyla bu çalışma bilime yapacağı genel katkı açısından önemlidir. Bu çalışmada istatistik eğitimine odaklanılmış ve mevcut durumuna dikkat çekilmiştir. Bu nedenle, bu çalışmanın istatistik eğitiminin kalitesinin artmasına katkı sağlayaması ve dolaylı olarak öğrencilerin gerçekleştirecekleri nicel çalışmalarının kalitesinin artırılmasına yardımcı olması beklenmektedir.

YÖNTEM

Bu bölümde araştırma deseni, araştırmada kullanılan değişkenler, katılımcı özellikleri, veri toplama araçları ve süreci, verilerin analizi bölümlerine yer verilmiştir.

Araştırmanın Deseni

Matematik başarısı, istatistiğe yönelik tutumlar ve istatistik kazanımları değişkenleri arasındaki yapısal ilişkileri inceyen bu çalışmada tarama deseni kullanılmıştır. Tarama deseni, katılımcıların tutum ve düşüncelerini anketler yoluyla elde ederek, nicel ve sayısal betimlemeler aracılığıyla sunulmasını sağlamaktadır (Creswell & Miller, 2000). Bu çalışmada da tarama deseni kullanılarak İstatistiğe yönelik Tutum Anketi© yoluyla çalışma verileri toplanmıştır.

Değişkenler

Çalışmanın değişkenleri matematik başarısı (geçmiş ve genel matematik başarısına ilişkin kişisel görüşler), istatistiğe yönelik tutumlar (duygu, bilşişsel yeterlilik, zorluk, değer, ilgi, çaba) ve istatistik kazanımlarıdır (istatistik dersinden alınan not, program boyunca istatistiği kullanma isteği, işe sahip olunduğunda istatistiği kullanma isteği).

Çalışamada test edilen İstatistik Tutum-Kazanım Modelinde matematik başarısı ve zorluk değişkeni dışsal değişkenler (exogenous variables), zorluk dışındaki istatistiğe yönelik tutum değişkenleri (duygu, bilişssel yeterlik, değer, ilgi, çaba) içsel değişkenler (endogenous variables) ve istatistik kazanımları değişkeni ise bağımlı değişkendir (outcome variable). Dışsal değişken olan zorluk ve matematik başarısı değişkenlerinin modelde belirtilen hiçbir değişken tarafından açıklanmadığı varsayıldığı için dışsal değişken olarak adlandırılmaktadır. İçsel değişkenlerin (duygu, bilişsel yeterlik, değer, ilgi, çaba) ise modelde belirtilen bazı değişkenler tarafından açıklandığı varsayıldığı için, bu değişkenler içsel değişken olarak adlandırılmaktadır. İstatik kazanımları değişkeni modelde belirtilen bazı değişkenler tarafından açıklanıp, hiçbir değişkeni açıklamadığı için modelin bağımlı değişkeni (outcome variable) olarak adlandırılmıştır.

Çalışma Grubu

Çalışma grubu, Türkiye'de bir üniversitede lisans ve yükseklisans eğitimi gören ve istatistik dersi alan toplam 247 öğrencidir. Katılımcıların alanları mühendislik (%26.3), eğitim (%23.1), iktisat (%13.8), psikoloji (%12.6), sosyoloji (%8.5), uygulamalı matematik (%4.9), ve işletmedir (%3.2). Kayıtlı oldukları diploma derecelerine bakıldığında, katılımcıların %63.2'si lisans, %23.1'i yükseklisans ve %9.3'ü doktora öğrencisidir. Ayrıca lisans öğrencilerinin %36'sı ikinci sınıf, %21.1'i üçüncü sınıf ve %6.1'i dördüncü sınıf öğrencisidir.

Veri Toplama Aracı

Veri toplamak amacıyla İstatistiğe Yönelik Tutum Anketi (SATS-36©; Schau, et al., 1995; Schau, 2003) veri toplama aracı olarak kullanılmıştır. Öğrencilerin istatistiğe yönelik tutumları İstatistiğe Yönelik Tutum Anketi'nin altı alt boyutu ile ölçülmüştür: duygu, bilişsel yeterlik, zorluk, değer, ilgi ve çaba. Öğrencilerin matematik başarıları ise İstatistiğe Yönelik Tutum Anketi'nde bulunan iki ek soru ile ölçülmüştür: "Geçmişte aldığınız matematik derslerinizde ne ölçüde başarılıydınız?" ve "Matematikte ne kadar başarılısınız?". Öğrencilerden bu iki soruyu 7'li Likert tipi ölçek üzerinde yanıtlamaları istenmiştir (1 = Çok başarısızdım / Çok başarısızım ve 7 = Çok başarılıydım / Çok başarılıyım). Öğrencilerin istatistik kazanımları, istatistik dersinden alınan not ile İstatistiğe Yönelik Tutum Anketi'nde bulunan iki ek soru ile ölçülmüştür: "Okulunuzu bitirene kadar istatistiği ne ölçüde kullanacaksınız?" ve "Mezun olup iş hayatınıza başladığınızda istatistiği ne kadar kullanacaksınız?" (1=Hiç kullanmayacağım, 7=Büyük ölçüde kullanacağım).

İstatistiğe Yönelik Tutum Anketi İtalya, Hollanda, İsrail, Güney Afrika gibi pek çok ülkede uygulanmış ve farklı dillere çevrilmiştir. Anketin farklı kültürlere uyarlandığı pek çok çalışmada ölçeğin psikometri özellikleri araştırılmıştır (Chiesi & Primi, 2008; Coetzee & van der Merwe, 2010; Hilton ve ark., 2004; Tempelaar ve ark., 2007; Verhoeven, 2009). Bu çalışmalardan bazılarında ölçeğin altı boyutlu yapısı doğrulayıcı faktör analizi ile test edilmiş ve ölçek yapısının toplanan verilerden elde edilen sonuçlara uyum gösterdiği bulunmuştur (Tempelaar ve ark., 2007; Verhoeven, 2009). Ölçeğin iç tutarlılığına bakıldığında ise Cronbach alfa katsayılarının yüksek olduğu rapor edilmiştir. Bu katsayılar ölçek altboyutlarından duygu için .80 ile 82, bilişsel yeterlik için .77 ile .82, değer için .78 ile .82, zorluk için .68 ile .75, ilgi için .80 ile .84, ve çaba için .76 ile .80 arasında değişmektedir (Tempelaar ve ark., 2007; Verhoeven, 2009).

İngilizce olan İstatistiğe Yönelik Tutum Anketi© katılımcılara uygulanmadan önce Türkçeye uyarlanmıştır. Anket uyarlama çalışmasında geri-çeviri yöntemi kullanılmıştır. İlk olarak ölçek, beş uzmandan görüş alınarak Türkçeye çevrilmiştir. Bu kişiler iki İngilizce öğretmeni, bir ölçme değerlendirme uzmanı yardımcısı doçent doktor, bir rehberlik ve psikolojik danışma uzmanı doktor ve bir öğretim programları ve öğretimi doktora öğrencisidir. Daha sonra, Türkçeye çevrilmiş olan ölçek üç uzman tarafından İngilizceye geri çevrilmiştir. Bu kişilerden ikisi program geliştirme ve öğretim anabilim dalı doktor adayları ile bir İngilizce öğretmenidir. Daha sonra, İstatistiğe Yönelik Tutum Anketi'nin orijinal İngilizce formu ile İngilizceye geri çevirilen formu karşılaştırılmıştır. İki form arasında yaklaşık %90 benzerlik görülerek Türkçeye uyaralanan ölçeğin orijinal ölçekle tutarlı olduğuna karar verilmiştir.

Türkçeye çevrilen ölçeğin geçerlik ve güvenirlik çalışmalarını yapmak için pilot çalışma gerçekleştirilmiştir. Pilot çalışmada 347 (% 59.4 bayan ve % 36 erkek) öğrenciden veri toplanmıştır. Pilot çalışmanın katılımcıları istatistik derslerini alan lisans (n= 231, % 66.57) ve lisansüstü eğitim gören (n=108, % 31.1) öğrencilerdir. Bu öğrenciler, eğitim (n=69), psikoloji (n=44), iktisat (n=108), işletme (n=31), mühendislik (n=70), ve uygulamalı matematik (n=23) alanlarında eğitim görmektedir. Pilot çalışmaya katılan iki öğrenci ise eğitim gördüğü alanı belirtmemiştir.

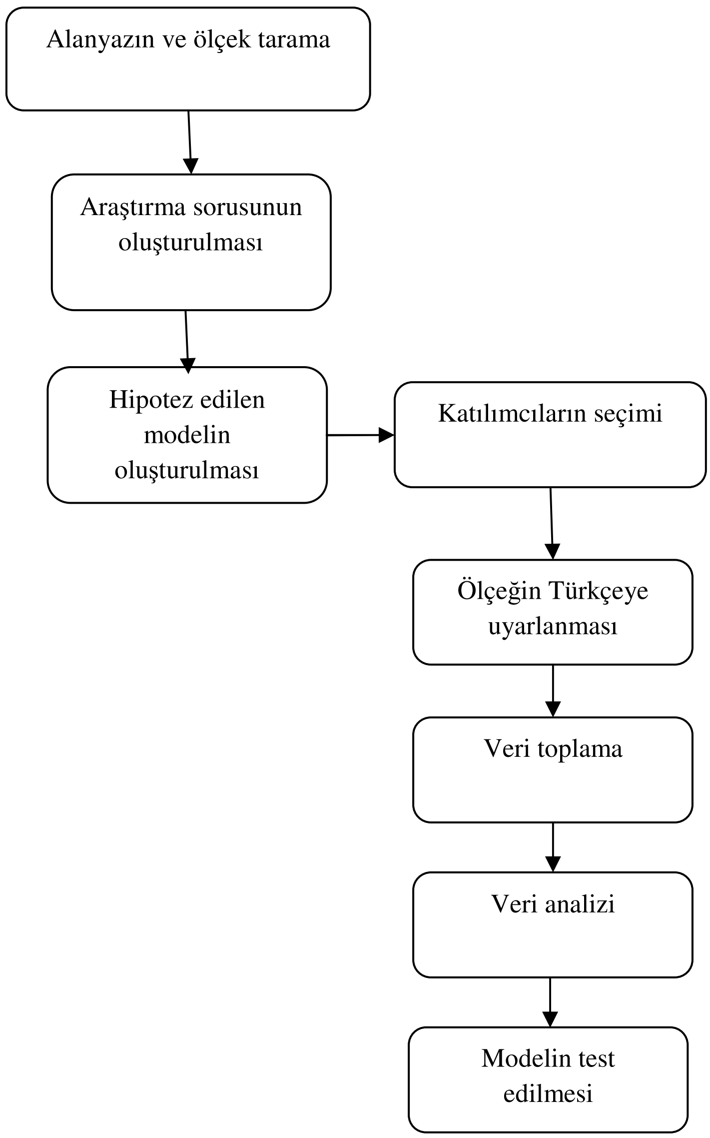
Türkçeye çevrilen İstatistiğe Yönelik Tutum Anketi'nin altı boyutlu (duygu, bilişsel yeterlik, zorluk, değer, çaba, ilgi) yapısını test etmek amacıyla doğrulayıcı faktör analizi uygulanmıştır. Analiz, Mplus programı (Muthen & Muthen, 2007) kullanılarak gerçekleştirilmiştir. Analiz sonucunda öngürülen ölçek alt boyutlarının katılımcılardan elde edilen verilerle uyum gösterdiği bulunmuştur. Buna göre model indeksleri şu şekilde bulunmuştur: $\chi^2(120)= 286.95$, $p<.05$, CFI = .95, SRMR = .07 ve RMSEA = .06 (%90 güven aralığında .05 ile .07 arasında). Elde edilen bu sonuçlar ölçeğin yapısal geçerliliğine ilişkin deliller sunmaktadır. Çünkü yukarıda belirtilen indeksler önerilen aralıklardadır. Örneğin CFI değerinin .90'dan büyük olması, SRMR ve RMSEA değerlerinin .10'dan küçük olması önerilmektedir (Kline, 2005).

Ayrıca factor yükleri incelendiğinde bulunan değerlerin. 43 ile. 90 arasında değiştiği ve bütün faktör yüklerinin istatistiksel olarak anlamlı olduğu görülmüştür. Pilot çalışmada doğrulayıcı faktör analizi sonucunda elde edilen bulgular alan yazınla tutarlıdır (Sorge & Schau, 2002; Tempelaar ve ark., 2007).

Türkçeye çevrilen İstatistiğe Yönelik Tutum Anketi©'nin güvenirlik analizi ölçek altboyutlarının Cronbach alfa katsayıları hesaplanarak gerçekleştirilmiştir. Katsayılar şu şekilde bulunmuştur: duygu = .85, bilişsel yeterlik = .82, değer = .85, zorluk = .69, ilgi = .90, çaba = .81. Bu sonuçlar, zorluk altboyutu güvenirlik katsayısının kabul edilebilir düzeyde ve diğer altboyutların ise yüksek düzeyde olduğunu göstermiştir (Kline, 2005). Bu sonuçlar, ölçeğin farklı dillerdeki uygulamalarıyla da tutarlılık göstermektedir (Carnell, 2008; Hilton ve ark., 2002; Tempelaar ve ark., 2007; Verhoeven, 2009).

Veri Toplama Süreci

Bu çalışmada, öğrencilerin istatistiğe yönelik tutumları, matematik başarıları üzerine kişisel görüşleri ve istatistik kazanımlarına yönelik veriler anket yoluyla toplanmış ve nicel analizler kullanılarak raporlanmıştır. Bu çalışmaya öncelikle geniş bir alan yazın taraması ile başlanmıştır. Alanyazın taraması sonucunda araşrıma sorusu oluşturulmuş ve daha sonra 36 madde ve altı alt boyuttan oluşan İstatistiğe Yönelik Tutum Anketi (SATS-36©; Schau, 2003) veri toplama aracı olarak seçilmiştir. Daha sonra hipotez edilen İstatistik Tutum-Kazanım Modeli oluşturulmuş ve çalışmanın hedef kitlesi seçilmiştir. Hedef kitle belirlendikten sonra ölçek Türkçeye uyarlanmış ve 2009-2010 güz ve bahar dönemleri sonlarında araştırma grubuna uygulanmıştır. Toplanan veriler, betimsel olarak ve Yapısal Eşitlik Modeli (YEM) kullanılarak analiz edilmiştir. Veri toplama süreci basamakları Şekil 2'de sunulmaktadır.



Şekil 2 Araştırma Deseninin Basamakları

Verilerin Analizi

Çalışmada hipotez edilen modeli test etmek amacıyla Yapısal Eşitlik modellemesi (YEM) gerçekleştirilmiştir. Analiz, Mplus programı kullanılarak yapılmıştır (Muthen & Muthen, 2007). Sonuçlar, farklı model indekslerine bakılarak yorumlanmıştır. Bunlar ki-kare, CFI, RMSEA, and SRMR ve parametre tahminleridir.

BULGULAR

Hipotez edilen İstatistik Tutum-Kazanım Modelini test etmeden önce yapısal eşitlik modellemesi yapılabilmesi için gereken sayıltıların sağlanıp sağlanmadığına bakılmıştır. Bu nedenle öncelikle kayıp verilerin miktarı ve dağılımına bakılmıştır. Daha sonra verilerdeki uç noktalar tespit edilerek verilerin çoklu normal dağılımına bakılmıştır. Ayrıca analize dâhil edilen değişkenler arasında doğrusal ilişkilerin olup olmadığı da kontrol edilmiştir ve son olarak değişkenler arasında aşırı yüksek ilişki olup olmamasına (multicollinearity) ve hata varyanslarının eşit dağılmasına bakılmıştır (homoscedasticity). Belirtilen sayıltıların kontrol edilmesi için SPSS 15 programı kullanılmıştır. Bu sayıltılardan çoklu normal dağılım dışında bir soruna rastlanmadığı görülmüş ve verilerin analize uygun olduğu sonucuna varılmıştır. Çoklu normallik sağlanmadığı için yapısal eşitlik modeli analizinde standart hatalardan ekilenmeyen 'en çok olabilirlik tahmin edicisi metodu' (maximum likelihood estimation with robust standard errors, MLR) kullanılmıştır.

a. Betimsel Sonuçlar

Betimsel istatistik analizleri sonucunda öğrencilerin çoğunun geçmiş (n=211, %85.4) ve genel (n=204, %83.5) matematik başarılarını yüksek olarak belirttikleri görülmüştür. Öğrenciler, mevcut istatistik derslerini geçmeyi beklediklerini (n=150, %60.6) belirtmiştir. Ayrıca öğrencilerin yarısından fazlası kayıtlı oldukları programa devam ettikleri sürece (n=135, %54.6) ve işe girdiklerinde (n=135, %54.6) istatistiği kullanacaklarını belirtmiştir. Katılımcılar mevcut istatistik derslerinden genel olarak ortalama düzeyde notlar almıştır ($\bar{X}$=4.86, SS=1.97). Öğrencilerin istatistiğe yönelik tutumları incelendiğinde ise genel olarak olumlu tutumlara sahip oldukları görülmektedir. Buna göre, dönem sonunda öğrencilerin istatistiğe yönelik duygularının ($\bar{X}$=4.60, SS=1.38), bilişsel yeterliliklerinin ($\bar{X}$=5.43, SS=1.07), istatistiği öğrenmek için gösterdikleri çabanın ($\bar{X}$=5.10, SS=1.27) ve istatistiğe verdikleri değerin ($\bar{X}$=5.02, SS=1.02) olumlu olduğu bulunmuştur. Bununla beraber, öğrencilerin istatistiğe yönelik ilgilerinin ($\bar{X}$=4.37, SS=1.57) ve istatistiğin zorluğuna yönelik tutumlarının ($\bar{X}$=3.52, SS=.88) tarafsız olduğu görülmüştür. Bu sonuçlar alanyazındaki bulgularla paralellik göstermektedir. Hollanda (Tempelaar et al, 2007), A.B.D. (Carnell, 2008), ve Güney Afrika'dan (Coetzee & van der Merwe, 2010) toplanan verilerle gerçekleştirilen çalışmalarda da benzer şekilde sonuçlar rapor edilmiştir. Betimsel sonuçlar ayrıca matematik başarısı değişkenin hiç bir tutum değişkeni ile anlamlı derecede ilişkili olmadığını fakat istatistik kazanımları değişkeni ile anlamlı derecede ilişkili olduğunu göstermiştir ($r=.14$, $p<.05$). İstatistiğe yönelik tutum değişkenlerinden zorluk dışındaki bütün değişkenlerin istatistik kazanımları değişkeni ile anlamlı derecede ilişkili olduğu bulunmuştur. Diğer bir değişle, istatistik kazanımları ile duygu ($r=.38$, $p<.05$), bilişsel yeterlik ($r=.35$, $p<.05$), değer ($r=.51$, $p<.05$), ilgi ($r=.57$, $p<.05$), çaba ($r=.44$, $p<.05$) değişkenleri arasında istatistiksel olarak anlamlı ilişki bulunmuştur.

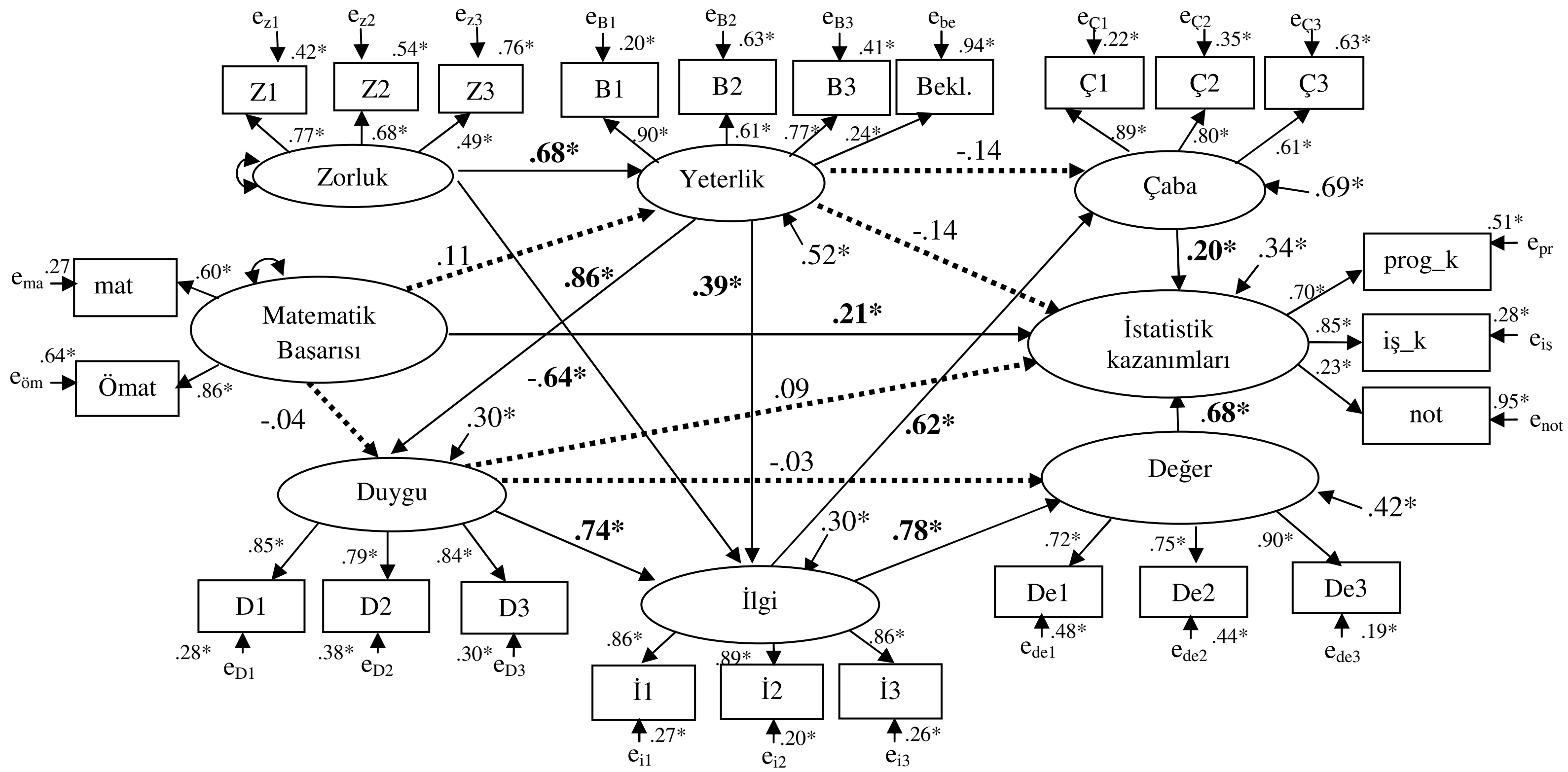
b. Yapısal Eşitlik Modeli Analizi

Araştırmada hipotez edilen İstatistik Tutum-Kazanım Modelini test etmek amacıyla yapısal eşitlik modellemesi (YEM) analizi gerçekleştirilmiştir. Hipotez edilen model iki basamakta test edilmiştir. Birinci basamakta ölçme modeli (measurement model) ikinci basamakta ise yapısal model (structural model) test edilmiştir.

İlk basamakta, ölçme modelinin test edilmesinde İstatistik Tutum-Kazanım modelinde yer alan faktörlerin (duygu, matematik başarısı, zorluk, bilişsel yeterlik, ilgi, çaba, değer, istatistik kazanımları) göstergeler (madde parselleri) tarafından ne ölçüde açıklandığı araştırılmıştır. Analiz sonuçlarını yorumlamak için çok sayıda model uyum indeksleri kullanılmıştır (MacCallum ve ark., 1996). Bunlar ki-kare, ki-kare/serbestlik derecesi, CFI, RMSEA, SRMR indeksleridir. Ki-kare değeri istatistiksel olarak anlamlı bulunmuştur, χ^2 (224) = 387.163, p<.05. Bu değer, tahmin edilen ölçme modelinin verilerin gösterdiği modelden anlamlı derecede farklı olduğunu göstermektedir. Ancak, yüksek katılımcı sayısının ki-kare testinde istatistiksel olarak anlamlı sonuçlara yol açtığı bilindiği için diğer indeksler de incelenmiştir. Ki-kare/serbestlik derecesi 1.73, CFI değeri .93, SRMR değeri .06 ve RMSEA değeri .05 (%90 güvenirlik aralığında .05 ile .06 arasında) olarak bulunmuştur. Bu sonuçlar, hipotez edilen ölçme modelinin elde edilen verilerle uyumlu olduğunu göstermiştir (Kline, 2005). Ölçme modelini test etmek amacıyla, ayrıca beta yüklerine (path coefficients) de bakılmıştır. Standardize edilmiş ve standardize edilmemiş beta yüklerinin hepsinin istatistiksel olarak anlamlı olduğu görülmüştür. Beta yüklerini yorumlamak için şu kriterler kullanılmıştır: standardize edilmiş beta yükü değerleri .10 civarında olduğunda küçük, .30 civarında olduğunda orta ve .50'den büyük olduğunda ise büyüktür (Kline, 2005). Bu çalışmada, standardize edilmiş beta yüklerinin .24 (orta) ile .91 (büyük) arasında değiştiği bulunmuştur. Böylece modeldeki faktörlerin (duygu, matematik başarısı, zorluk, bilişsel yeterlik, ilgi, çaba, değer, istatistik kazanımları) hipotez edilen ölçme modeli tarafından anlamlı derecede açıklandığını görülmüştür.

İkinci basamakta, yapısal modeli test etmek amacıyla çok sayıda model uyum indeksleri kullanılmıştır. Bunlar ki-kare, ki kare/serbestlik derecesi, CFI, RMSEA, SRMR indeksleridir. Ki-kare değeri istatistiksel olarak anlamlı bulunmuştur, χ^2(235)=409.761, p<.05. Diğer model uyum indeksleri ise ki-kare/serbestlik derecesi= 1.74, CFI=.93, SRMR=.07 ve RMSEA=.06 (%90 güvenirlik aralığında .05 ile .06 arasında) şeklindedir. Bu değerler, hipotez edilen yapısal modelin yani İstatistik Tutum- Kazanım modelinin araştırma verilerine uyumlu olduğunu göstermiştir (Kline, 2005). Yapısal modeldeki beta yükleri, içsel değişkenlerin (endogenous variables) modeldeki diğer değişkenler tarafından doğrudan nasıl yordandığını açıklayan regresyon katsayıları olarak yorumlanmaktadır. Bunlara ayrıca direk etki (doğrudan etki) de denilmektedir. Beta yükleri incelendiğinde hipotez edilen İstatistik Tutum-Kazanım Modelindeki toplam 16 yoldan 10'unun istatistiksel olarak anlamlı olduğu görülmüştür. Çalışmada istatistiksel olarak anlamlı olmayan yollar matematik başarısından bilişsel yeterlik ve duyguya olan; bilişsel yeterlikten çaba, duygu ve değere, ve bilişsel yeterlik ve duygudan istatistik kazanımlarına olan yollardır. İstatistiksel olarak anlamlı olan yol katsayıları ise .20 (küçük) ve .86 (büyük) değerleri arasında değişmektedir. Çalışmada istatistiksel olarak anlamlı olan yollara (direk etki/doğrudan etki) bakıldığında elde edilen sonuçlar şu şekildedir (Şekil 3):

1. Zorluk değişkeninin bilişsel yeterlik üzerine olan direk etkisi büyüktür (68).
2. Zorluk değişkeninin ilgi değişkeni üzerine direk etkisi büyüktür (-64).
3. Bilişsel yeterlilik değişkeninin ilgi değişkeni üzerine direk etkisi orta derecededir (.39).
4. Duygu değişkeninin ilgi değişkeni üzerine direk etkisi büyüktür (.74).
5. Bilişsel yeterlik değişkeninin duygu değişkeni üzerine direk etkisi büyüktür (.86).
6. İlgi değişkeninin çaba değişkeni üzerine direk etkisi büyüktür (.62).
7. İlgi değişkeninin değer değişkeni üzerine direk etkisi büyüktür (.78).
8. Çaba değişkeninin istatistik kazanımları değişkeni üzerine direk etkisi küçüktür (.20).
9. Matematik başarısı değişkeninin istatistik kazanımları üzerine direk etkisi küçüktür (.21).
10. Değer değişkeninin istatistik kazanımları üzerine direk etkisi büyüktür (.68).



Şekil 3 İstatistik Tutum-Kazanım Modeli Standardize Edilmiş Değerler - - -▸ istatistiksel olarak anlamlı olmayan yollar, ⟶ , istatistiksel olarak anlamlı olan yollar, *p<.05. Note. D1-D2: Duygu , Yeterlik: Bilişsel Yeterlik, B1-Bekl.: Bilişsel yeterlik, Bekl.= Başarı beklentisi, De1-De3: Değer, Z1-Z3: Zorluk, Ç1-Ç3: Çaba; İ1-İ3: İlgi, Ömat=Önceki matematik başarısı, mat=Matematik başarısı, iş_k= işe sahip olunduğunda istatistiği kullanma isteği, prog_k= program boyunca istatistiği kullanma isteği, not = istatistik dersinden alınan harf notu.

Dolaylı etkiler, direk etkilerden yola çıkılarak hesaplanmaktadır. Bu çalışmada, zorluk değişkeninin ilgi değişkeni üzerine bilişsel yeterlik yoluyla olan dolaylı etkisi pozitif yönde iken direk etkisi negatif yöndedir. Ayrıca bilişsel yeterlik değişkeninin istatistik kazanımları üzerine dolaylı etkisi istatistiksel olarak anlmalı değilken ilgi değişkeni yoluyla olan dolaylı etkisi istatistiksel olarak anlamlıdır. Benzer durum duygu değişkeni için de görülmektedir. Duygu değişkeninin değer ve istatistik kazanımları üzerine direk etkisi anlamlı değilken yine ilgi yoluyla olan dolaylı etkisi istatistiksel olarak anlamlıdır.

Değişkenler arasındaki direk ve dolaylı etkiler toplandığında toplam etki değerleri elde edilmiştir (Kline, 2005). Bu çalışmanın bağımlı değişkeni istatistik kazanımları olduğu için istatistik kazanımları değişkeni üzerine olan toplam etkileri hesaplamak önemlidir.

Duygu, bilişsel yeterlik, ilgi ve değer değişkenlerinin istatistik kazanımları değişkeni üzerine toplam etki değerinin yüksek olduğu bulunmuştur. Duygu, bilişsel yeterlik, ilgi ve değer değişkenlerinin istatistik kazanımları değişkeni üzerine toplam etki değerleri sırasıyla .56, .56, .65 ve .68'dir.

Matematik başarısı ve çaba değişkenlerinin istatistik kazanımları değişkeni üzerine toplam etki değerleri ise sırasıyla .25 ve .20'dir ve orta derecededir.

Sadece zorluk değişkeninin istatistik kazanımları değişkeni üzerine toplam etki değeri istatistiksel olarak anlamlı değildir. Değişkenler arasındaki doğrudan, dolaylı ve toplam etki değerleri Tablo 1'de özetlenmiştir.

Tablo 1

Standardize Edilmiş Doğrudan, Dolaylı ve Toplam Etkiler

		Duygu	Bilişsel yeterlik	İlgi	Çaba	Değer	Istatistik Kazanım.
Matematik başarısı	Doğrudan Etki	-.04	.11	-	-	-	.21*
	Dolaylı Etki	.09	-	.01	-.02	.00	.04
	Toplam Etki	.05	.11	.01	-.02	.00	.25*
Zorluk	Doğrudan Etki	-	.68*	-.64*	-	-	-
	Dolaylı Etki	.58*	-	.69*	-.49*	-.50*	-.10
	Toplam Etki	.58*	.68*	.05	-.49*	-.50*	-.10
Duygu	Doğrudan Etki	-	-	.74*	-	-.03	.09
	Dolaylı Etki	-	-	-	.46*	.58*	.46*
	Toplam Etki	-	-	.74*	.46*	.55*	.56*
Bilişsel yeterlik	Doğrudan Etki	.86*	-	.39*	-.14	-	-.14
	Dolaylı Etki	-	-	.64*	.64*	.28	.70*
	Toplam Etki	.86*	-	1.03*	.50*	.28	.56*
İlgi	Doğrudan Etki	-	-	-	.62*	.78*	-
	Dolaylı Etki	-	-	-	-	-	.65*
	Toplam Etki	-	-	-	.62*	.78*	.65*
Çaba	Doğrudan Etki	-	-	-	-	-	.20*
	Dolaylı Etki	-	-	-	-	-	-
	Toplam Etki	-	-	-	-	-	.20*
Değer	Doğrudan Etki	-	-	-	-	-	.68*
	Dolaylı Etki	-	-	-	-	-	-
	Toplam Etki	-	-	-	-	-	.68*

*p<.05

Son olarak, her bir değişken için model tarafından açıklanan varyanslar, çoklu korelasyon katsayısının karesine (R^2) bakılarak incelenmiştir. Buna göre, hipotez edilen İstatistik Tutum-Kazanım Modelinin bütün faktör varyanslarını istatistiksel olarak anlamlı derece açıkladığı ve çalışmanın bağımlı değişkeni olan istatistik kazanımlarının varyansını ise %66'sını açıkladığı bulunmuştur (Tablo 2).

Tablo 2

Çoklu Korelasyon Kareleri

Değişken	*Tahmin*	*Standart Hata.*
Bilişsel yeterlik	.48*	.07
Çaba	.31*	.06
İlgi	.70*	.07
Duygu	.73*	.07
Değer	.58*	.06
İstatistik kazanımları	.66*	.09

*p<.05

TARTIŞMA

Bu çalışmada matematik başarısı, istatistiğe yönelik tutumlar, ve istatistik kazanımları arasındaki ilişkiler hipotez edilen İstatistik Tutum-Kazanım Modeli test edilerek incelenmiştir.

Genel model uyumuna bakıldığında hipotez edilen İstatistik Tutum-Kazanım Modeli'nin elde edilen verilerle uyumlu olduğu bulunmuştur. Modelde yer alan her faktörün model tarafından istatistiksel olarak anlamlı derecede açıklandığı görülmüştür. Bağımlı değişken olan istatistik kazanımları faktörünün varyansı ise model tarafından yine istatistiksel olarak anlamlı derecede ve % 66'sı açıklanacak şekilde yordanmıştır.

Modelin genel olarak çalışma verilerine uyum sağlamasının yanı sıra, modelde yer alan faktörlerin modele yaptığı katkılara da bakılmıştır. Buna göre, ilgi ve değer değişkenlerinin istatistik kazanımları değişkeni üzerine en yüksek ve istatistiksel olarak anlamlı toplam etki değerine sahip olduğu bulunmuştur. Duygu ve bilişsel yeterlik değişkenlerinin istatistik kazanımları değişkeni üzerine toplam etki değerlerinin ise ikinci derecede büyük ve istatistiksel olarak anlamlı olduğu bulunmuştur. Ayrıca, çaba ve matematik başarısı değişkenlerinin istatistik kazanımları değişkeni üzerine toplam etki değeri orta derecede ve anlamlıdır. Zorluk değişkeninin istatistik kazanımları değişkeni üzerine toplam etki değeri ise istatistiksel olarak anlamlı değildir.

Çalışmanın sonuçları, istatistik kazanımları değişkeninin öğrencilerin istatistiğe duydukları ilgi ve istatistiğe verdikleri değer tarafından yüksek ölçüde yordandığını göstermiştir. Öğrencilerin istatistik üzerine bilişsel yeterlilikleri ile ilgili tutumları ve istatistiğe yönelik duyguları da onların istatistik kazanımlarını açıklayan faktörler olarak bulunmuştur. Ayrıca öğrencilerin matematik başarıları üzerine kişisel görüşleri ve istatistik derslerinde gösterdikleri çaba da istatistik kazanımlarını açıklayan faktörler arasındadır. Çalışmada bulunan ilginç bir bulgu öğrencilerin istatistiğin zorluğuna ilişkin görüşlerinin istatistik kazanımları üzerine toplam etkisinin bulunmamasıdır. Ancak öğrencilerin istatistiğin zorluğuna ilişkin görüşlerinin onların istatistiğe yönelik duygularını, bilişsel yeterliklerini, istatistiğin değerine ilişkin tutumlarını ve istatistik derslerinde göstermiş oldukları çabayı açıklamada etkili olduğu bulunmuştur. Bu açıdan bakıldığında modelde yer alan tüm değişkenlerin İstatistik Tutum-Kazanım Modeli'ninde hipotez edildiği gibi istatistik kazanımları bağımlı değişkenini açıklamada önemli rolleri olduğunu söylemek mümkündür.

Öneriler

Kuram ve uygulamaya yönelik öneriler aşağıda verilmiştir:

1. Bu çalışma Türkiye'de İngilizce eğitim veren yüksek prestijli bir üniversitenin lisans ve yükseklisans öğrencileriyle gerçekleştirilmiştir. Bu nedenle çalışmanın bulguları hedef kitle olan çalışmanın yürütüldüğü üniversitenin istatistik dersi alan lisans ve yükseklisans öğrencilerine genellenmektedir. Gelecekte yapılacak çalışmalarda bu ilişkilerin farklı öğrenci profilleriyle araştırılarak daha geniş kitlelere

genellenmesi önerilmektedir. Ayrıca, bu çalışmadan yola çıkılarak kültürler arası karşılaştırma çalışmaları gerçekleştirilebilir ve böylece bu çalışmada öne sürülen değişkenler arası ilişkilerin farklı kültür ve farkı örneklemler için durumu incelenebilir.

2. Bu çalışmada yer alan matematik başarısı değişkeni katılımcıların geçmiş ve güncel matematik başarıları üzerine kişisel görüşleri alınarak ölçülmüştür ve çalışmanın sonucunda öğrencilerin matematik başarıları üzerine kişisel görüşlerinin onların istatistikle ilgili duyguları ve bilişsel yeterlikleri üzerine etkisi olmadığı ancak istatistik kazanımları üzerine etkisi olduğu bulunmuştur. Benzer şekilde çalışmanın bağımlı değişkeni olan istatistik kazanımlarının öğrencilerin istatistik dersinden aldıkları notlar ve gelecekte işe sahip olduklarında ve eğitim aldıkları program boyunca istatistiği kullanma istekleri ile ölçülmüştür. Gelecekte yapılacak çalışmalar için matematik başarısı değişkenini ve öğrencilerin ileride istatistiği kullanma durumlarının doğrudan yollarla ölçülmesi önerilmektedir. Örneğin, matematik başarısını ölçmek için başarı testleri uygulanabilir ve öğrencilerin gelecekte aldıkları istatistik ders sayıları takip edilerek, farklı zamanlarda istatistiği ne kadar kullandıkları ölçülebilir.

3. Bu çalışmada öğrencilerin istatistik dersinden aldıkları notlar dışındaki bütün değişkenler tek bir zaman aralığında ölçülmüştür. Bu nedenle çalışmada incelenen değişkenler neden-sonuç ilişkilerini önermek yerine o anki durağan ilişkileri göstermektedir. Buna bağlı olarak, gelecekte yapılan çalışmalarda boylamasına desenler kullanılarak verilerin öğrencilerin istatistik dersini almadan önce, istatistik dersini aldıkları sırada ve daha sonra gibi farklı zamanlarda toplanılması önerilmektedir.

4. Çalışmada hipotez edilen İstatistik Tutum-Kazanım Modeli değişkenler arasındaki tek yönlü ilişkileri içermektedir. Gelecekte yapılacak çalışmalarda iki yönlü ilişkilerin de incelenmesi önerilmektedir. Örneğin, bu çalışmada öğrencilerin bilişsel yeterliliklerinin istatistik kazanımları üzerine etkisine bakılmıştır. Diğer çalışmalarda istatistik kazanımlarının öğrencilerin istatistiğe yönelik bilişsel yeterlikleri üzerine etkisine bakılması da önerilebilir.

5. Bu çalışmada gerçekleştirilen kapsamlı alanyazın taraması göstermiştir ki yapısal eşitlik modellemesi çalışmalarının büyük bir kısmında bağımlı değişken olarak istatististik başarısını kullanılmıştır (örneğin, Bude´ ve ark., 2007; Lalonde & Gardner, 1993; Nasser, 2004; Sorge, 2001). Oysaki öğrencilerin istatistiğe yönelik tutumları da istatistik dersinden sonraki davranışlarını etkileyen önemli bir faktör olarak görülmektedir (Gal, Ginsburg, & Schau, 1997). Bu nedenle bu çalışmada ele alınan bağımlı değişken öğrencilerin istatistik dersinden aldıkları notun yanı sıra, ileride istatistiği kullanma isteklerini de içermektedir. Gelecekte yapılacak çalışmalar için bu çalışmaya benzer şekilde farklı bağımlı değişkenler kullanılması önerilmektedir.

6. İstatistik Tutum-Kazanım Modeli'nde yer alan değişkenler çalışmanın bağımlı değişkeni olan istatistik kazanımlarını istatistiksel olarak anlamlı derecede yordamıştır. Fakat bazı demografik değişkenlerin (cinsiyet ve yaş gibi) ya da kişilik özelliklerinin (mükemmelliyetçilik ve öğrenme stilleri gibi) de istatistik kazanımlarını açıklamada rolü olduğu bilinmektedir (Onwuegbuzie & Daley, 1999; Tempelaar, Rienties, Loeff, & Giesbers, 2010). Çalışmada test edilen İstatistik Tutum-Kazanım Modeli'i yapılan analizler sonucunda toplanan verilerle uyum göstermiş olmasına rağmen, bu durum modelin hipotez edilen ilişkileri açıklayan en iyi model olduğunu göstermemektedir. Bu

nedenle gelecekte yapılacak çalışmalarda farklı alternatif modellerin test edilmesi önerilmektedir.

7. Bu çalışmada hipotez edilen ve test edilen İstatistik Tutum-Kazanım Modeli Eccles ve arkadaşlarının (Eccles & Wigfield, 1995, 2002; Wigfield & Eccles, 2000) beklenti-değer teoriesine dayanmıştır. Bu çalışma, Eccles ve arkadaşlarının modelinin istatistik eğitimine uygulanabileceğini göstermiştir. İstatistik Tutum-Kazanım Modelinin temel adığı kuramsal altyapı göz önünde bulundurulduğunda, bu modelin ileriki çalışmalarda Fen ve Matematik gibi diğer alanlara da uyarlanması önerilebilir.

8. Bu çalışma, öğrencilerin matematik başarıları üzerine kişisel görüşlerinin, onların istatistik kazanımlarını açıklamada etkili olduğunu göstermiştir. Buna bağlı olarak, istatistik eğitmenlerinin öğrencilerin matematik başarısı seviyelerinin farkında olmaları ve istatistik öğretimini bu faktörü göz önünde bulundurarak ayarlamaları önerilmektedir.

9. Çalışmada öğrencilerin istatistiğin değerine yönelik tutumları, istatistiğe duydukları ilgilerinin, bilişsel yeterliklerinin ve duygularının istatistik kazanımlarını açıklamada etkisinin olduğunu göstermiştir. Buna bağlı olarak, istatistik eğitmenlerinin öğrencilerin istatistiğin değerine yönelik tutumlarını artıracak değer biçme yöntemi (value-reappraisal method) gibi öğretim yöntemlerini (Acee & Weinstein, 2010) kullanmaları önerilmektedir. Ayrıca öğrencilerin istatistiğe yönelik olumlu duygularını ve istatistiğe olan ilgilerini artırmaları için öğrencilerin ilgilerini çekebilecek eğlenceli ve ilgi çekici yöntemler kullanmaları önerilmektedir (Berk & Nanda, 1998; Lesser & Pearl, 2008; Milburn, 2007).

10. Çalışmada öğrencilerin istatistiğe yönelik bilişsel yeterliklerinin onların istatitik kazanımlarını açıklamaya etkisi olduğu bulunmuştur. Bu nedenle istatistik eğitimcilerinin öğrencilerin bilişsel yeterlikleri hakkındaki görüşlerinin farkında olmaları ve öğretimi farklı seviyedeki ve farklı bilişsel yeterlik algısına sahip öğrencileri göz önünde bulundurarak planlamaları ve uygulamaları önerilmektedir.

11. Bu çalışma öğrencilerin istatistik başarının yanı sıra onların istatistiğe yönelik tutumlarının da istatistik eğitiminde önemli faktörler olduğunu göstermiştir. Bu nedenle istatistik eğitmenlerinin öğrencilerin istatistik başarılarının yanında istatistiğe yönelik tutumlarını da atırmayı hedeflemeleri ve öğrencilerinin istatistiğe yönelik tutumlarını ölçerek, farkındalık kazanmaları önerilmektedir.

APPENDIX K

CURRICULUM VITAE

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EDUCATION

2005-2011	METU	Integrated PhD
2000-2004	Elementary Science Education, Gazi University, Turkey	B.Sc.
1997-2000	Nigde Anatolian High School	High School

WORK EXPERIENCE

2005-2011	METU	Research/Teaching Assistant
2008-2009	University of California, Santa Barbara	Visiting Scholar
2004-2005	TED Ankara College	Assistant of Curriculum Development Expert

PUBLICATIONS

<u>Papers</u>

Emmioglu, E., & Capa-Aydin, Y (2011, August). *A meta-analysis on students' attitudes toward statistics*. Paper presented at 58th World Statistics Congress of the International Statistical Institute, Dublin,

Ireland.

Schau, C., & Emmioglu, E. (2011, August). *Changes in U.S. students' attitudes toward statistics across introductory statistics courses*. Paper presented at 58th World Statistics Congress of the International Statistical Institute, Dublin, Ireland.

Emmioglu, E., Capa-Aydin, Y., & Cobanoglu, R. (2010, September). *The relationship between graduate students' attitudes toward statistics and statistics achievement.* Paper presented at National Congress of Educational Sciences, Cyprus International University, Lefkosa, Cyprus.

Ramirez, C., Emmioglu, E., & Schau, C. (2010, August). *Understanding students' attitudes toward statistics: New perspectives using an expectancy-value model of motivation and the Survey of Attitudes Toward Statistics©*. Topic contributed paper presented at Joint Statistical Meetings, Section on Statistics Education, Vancouver, BC, Canada.

Capa-Aydin, Y, & Emmioglu, E. (2009, April). *The role of emotional regulation processes in Turkish high school students' achievement.* Paper presented at Annual Meeting of American Educational Research Association, San Diego, CA.

Keser, F., Akar, H., & Emmioglu, E (2009, September). *Building active citizens in school context through extra-curricular activities.* Paper presented at European Conference on Educational Research, Vienna, Austria.

Capa-Aydin, Y, & Emmioglu, E. (2008, September). *High school students' emotions and emotional regulation during test taking.* Paper presented at the European Conference on Educational Research, Gothenburg, Sweden.

Capa-Aydin, Y, & Emmioglu, E. (2008, May). *Students' views on assessment techniques used in statistics courses*. Paper presented at the National Congress of Measurement and Evaluation in Education and Psychology, Ankara University, Ankara, Turkey.

Emmioglu, E., Keser, F., Akar, H., & Yildirim, A. (2008, April). *Active citizenship training classroom activities.* Paper presented at the Conference of Good Examples in Education, Sabanci University, Istanbul, Turkey.