Undergraduate Social Sciences Students' Attitudes Toward Statistics

by

Asal Aslemand

A thesis submitted in conformity with the requirements
for the degree of Doctor of Philosophy
Department of Curriculum, Teaching and Learning
Ontario Institute for Studies in Education of the
University of Toronto

Undergraduate Social Sciences Students' Attitudes Toward Statistics

Asal Aslemand
Doctor of Philosophy, 2018

Department of Curriculum, Teaching and Learning
Ontario Institute for Studies in Education of the
University of Toronto

Abstract

This study investigated the changes in undergraduate social sciences students' attitudes toward statistics in an introductory statistics course for social science students. The relationships between students' attitudes toward statistics and their past mathematics achievement, their statistics outcomes, their sex, and their year of study were also investigated. The Survey of Attitudes Toward Statistics (SATS-36©) was used to collect data on students' attitudes toward statistics.

The study found no significant differences between male and female students' attitudes toward statistics. Moreover, no significant differences in attitudes were found by year of study of the participants. By the end of their introductory statistics course, students' attitudes improved for those students with low initial scores regarding their feelings concerning statistics, their competency in doing statistics, their valuing of the subject in their personal and professional lives, their perception of the difficulty of the subject, and their efforts to learn statistics. However, their interest in statistics remained the same. Students' attitudes-scores dropped for those students with high initial responses regarding their competency to do statistics, their valuing of the subject, and their interest in statistics. Their feelings concerning statistics, their perception of the difficulty of the subject, and their effort to learn statistics remained the same.

Students' past mathematics achievement, their valuing of, and their effort to learn statistics predicted their statistics outcomes by the end of the course. Additionally, students'

interest in statistics predicted their effort to learn statistics and their valuing of the subject by the end of the course, which contributed to their statistics outcomes. The results also revealed that, students' past mathematics achievement, and their perception of the difficulty of the subject predicted their cognitive competence in statistics, and their cognitive competence predicted their affect toward statistics by the end of the course.

Acknowledgements

I would to like to give a heartfelt thank you to my supervisor, Dr. Doug McDougall, for his positive approach to guiding me and making me feel confident in conducting research in mathematics education. Doug, I appreciate your endless support and the community of graduate students in mathematics education that you have organized and inspired at OISE.

I would like to thank my committee members, Drs. Clive Beck and Jim Hewitt, for providing their thoughtful and positive feedback to my thesis. Clive, I appreciate taking two courses with you at OISE. I learned about what it means to grow as a teacher, and how important it is to reflect on teaching. Jim, I thank you for providing careful feedback regarding my thesis and its statistical analyses. I would like thank Dr. David Booth for his participation in my thesis final oral examination and for providing valuable feedback to my work. Thank you kindly to my External Examiner, Dr. George Gadanidis for his insightful assessment of my dissertation.

I would like to sincerely thank Dr. Alison Gibbs for introducing me to the field of statistics education. Alison, I admire your positive attitude, dedication and innovative ideas to improve teaching and learning of statistics. I would also like to thank Dr. Candace Schau for permitting me to use the Survey of Attitudes Toward Statistics and for being available to answer my questions. I would like to thank Dr. Sohee Kang for her encouragement and for providing me with a research assistant, Olivia Rennie who did a great job at recruiting the participants for this study, and managing all aspects of data collection.

I would like to thank Prof. Olga Fraser for introducing me to learning statistics and for providing me with a forever-memorable teaching opportunity as her teaching assistant. I would also like to thank Dr. Alison Weir for her talented approach to teaching statistics. Alison, I enjoyed taking statistics courses with you and working alongside you as your teaching assistant.

Thank you to Prof. Jerry Brunner for his passion and dedication to teaching statistics. Jerry, I absolutely loved and appreciated completing all your assignments – they had embedded in them interesting statistical discoveries. Thank you to Dr. Monique Herbert for her passion to teaching statistics. Monique, I always looked forward to attending your classes. I would like to thank Dr. Stuart Kamentesky for his endless support and guidance in my academic journey.

Thank you to Prof. Mike Evans for providing me with the opportunity to teach an introductory statistics course at UTSC. I would also like to thank Profs. Mahinda Samarakoon and Ken Butler for being tremendous models of teaching for me at UTSC. You have taught me how to think about illustrating statistical concepts in interesting ways to students. I appreciate all the precious conversations that we had, which helped me reflect on and improve my teaching.

I would like to thank and acknowledge the support of Prof. David Fleet, Dr. Elaine Khoo, Dr. Gun Ho Jang, Dr. Michele Millar, Andrea Carter, Cheryl Clarke, Dannay Cavanagh, and Kelly Squier. Thank you to Elder Cat Criger for listening to my challenges and for shifting my views to think positively about way of life. I would like to acknowledge Dr. Margaret Easto Kidd whose quote: "If you love something, teach it to a friend" has resonated with me throughout my PhD journey. I believe in this quote and will cherish it forever.

To my dear family, Mom, Dad, and my brother, I thank you so ever much for being always supportive and for believing that I can finish this challenging and yet meaningful journey. This journey would have not been doable without your endless support and your encouragement. I dedicate this thesis to my very talented Mother, who is my greatest teacher and friend in life, who inspires me everyday, whose kindness and warmth is beyond measure, who has taught me how to persevere in the face of adversity, to be happy and joyful in life, and to be kind and respectful to all beings. I admire you Mom and strive for being a woman like you.

Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter One: Introduction

1.1 Introduction

Statistical messages play important roles in our lives, "either personally or in our social experience" (Hacker, 2016, p. 169). We need to be statistically literate and possess questioning ability (Gal, 2002; Rumsey, 2002; Utts, 2003) to "consume and critically digest the wealth of information" (Rumsey, 2002, p. 33) we are exposed to on a regular basis. Without the capacity to interpret and question statistics, we may be misled by those who are capable of producing numbers such as averages or percentages (Cerrito, 1999), and may thus solely become consumers of statistical information (Gal, 2002). Hacker (2016) asserts: "We should ask where [statistics] come from, how they were assembled, why they are being gathered, and how far they can be trusted" (p. 183). He stresses that all citizens should possess basic statistical knowledge that will support their understanding of "*public statistics*" (p. 169).

Undergraduate students in social sciences need to be equipped with basic statistical knowledge so that they can read and understand the statistical information presented in published articles. However, understanding basic statistical information is difficult for them to grasp (Lalayants, 2012) because they lack the appropriate prior mathematical knowledge, or have low confidence in doing mathematics, and therefore need extra support learning statistical ideas (Davis & Mirick, 2015; Lalayants, 2012; Malik, 2015). The difficulties that undergraduate social sciences students experience with learning statistical ideas may also be a result of the examples that instructors select to explicate concepts. If the chosen examples fail to illustrate the value (usefulness, relevance, and worth) of the subject to students' field of study, they may become uninterested in learning statistics and connecting statistical ideas to their program of study (Murtonen & Lehtinen, 2003).

In the current study, I assessed undergraduate social sciences students' attitudes toward statistics in an introductory statistics course for the social sciences at a large urban university. The approach to teaching statistics employed in this course aimed at increasing students' interest and engagement with course contents while demonstrating the relevance of learning statistics in the field of social sciences. I chose this particular group of students—undergraduate students in the social sciences programs—because, through my teaching experiences, I realized that these students confronted many challenges like the ones described by Lalayants (2012) and Murtonen and Lehtinen (2003).

In this chapter, I will describe the research context, the course under study, purpose of the study, research questions, significance of the study, my personal background as the researcher, the limitations of the study, and the structure of my thesis.

1.2 Research Context

In Ontario, a majority of the undergraduate students in the social sciences completed their high school diploma in Ontario. According to the Ontario Schools Kindergarten to Grade 12 *Policy and Program Requirement* document in 2016, in order to receive the Ontario Secondary School Diploma (OSSD), high school students are required to take three mathematics courses, with at least one mathematics course in grade 11. The humanities and social sciences programs offered at some universities do not require students to complete a grade 12 mathematics course. Therefore, prospective humanities and social sciences students are less likely to take a grade 12 mathematics course than they would be if grade 12 mathematics was required.

The grade 12 mathematics of data management, a current course in the Ontario curriculum, is considered to be adequate preparation for an introductory statistics course at the post-secondary level. However, this course is ignored by a majority of the future humanities and social sciences students who are not required to take a grade 12 mathematics course as part of their OSSD requirement, and as part of their admission criteria to Ontario universities. Therefore, in general, students in the humanities and social sciences fields at universities tend to have low levels of prior mathematical and statistical knowledge, which can affect their confidence in doing either mathematics or statistics as part of their curriculum (Lalayants, 2012; Malik, 2015; Murtonen & Lehtinen, 2003; Slootmaeckers, Kerremans & Adriaensen, 2014).

Most of the social sciences students often avoid taking their required introductory statistics course in their first year of program of study and instead will take this course in an upper or final year of their study. Therefore, for most of these students, there will be an estimated three to five year gap since their last high school mathematics course.

Adults who are poorly-equipped with basic mathematical knowledge, or who have forgotten the basics are faced with academic and professional challenges (Reston, 2007; Steen, 2001). They will experience difficulties understanding, communicating and following claims presented to them in the form of tables or graphs in research articles (Gal, 2002; Murtonen & Lehtinen, 2003; Reston, 2007). Thus, they will likely accept numerical information without the ability to justify, take a critical stance, or question the validity of statistical messages (Gal, 2002; Hampden-Thompson, & Sundaram, 2013).

In addition to their lack of adequate mathematical knowledge, students perceive an introductory statistics course as a rigorous mathematical course and therefore exhibit anxiety toward learning statistics (Malik, 2015; Onwuebuzie & Wilson, 2003; Zeidner, 1991). Their anxiety toward the subject of statistics stems from their previous related achievements or experiences in mathematics at the primary, middle or secondary school level (Lalayants, 2012; Malik, 2015; Murtonen & Titterton, 2004; Warwick, 2008).

Negative experiences of mathematics are often related to the ways in which students perceive themselves as learners of mathematics (Murtonen & Titterton, 2004; Warwick, 2008). For example, they might perceive themselves as incapable of doing mathematics, and therefore fear the subject, which can in turn make them feel anxious at the prospect of learning statistics (Gal, Ginsburg & Schau, 1997; Lalayants, 2012; Malik, 2015). Additionally, repeated failures to perform well in mathematics decrease students' confidence in doing mathematics (Warwick, 2008) and negatively relates to students' attitudes toward statistics (Gal & Ginsburg, 1994; Lalayants, 2012; Murtonen & Titterton, 2004). Thus, students with unpleasant mathematical experiences who harbour negative views about statistics may become less confident in their capabilities to apply their statistical skills and knowledge outside of a statistics classroom in their field of study and in their future profession (Schau, 2003b; Slootmaeckers et al., 2014).

However, students with successful previous mathematics achievements perceive themselves as intelligent and knowledgeable individuals who can understand and learn mathematical concepts (Arumugan, 2014; Dempster & McCorry, 2009; Warwick, 2008). Some studies have shown that students' statistics course outcomes are positively related to their previous achievement in mathematics courses (Chiesi & Primi, 2010; Emmioglu, 2011; Sorage & Schau, 2002). For those students with high previous mathematics achievements in particular, statistics course grades at the end of the course were very high (Carmona, Martinez & Sanchez, 2005). Also, students with more mathematical training obtained higher grades in their statistics course (Cashin & Elmore, 2005).

Research in statistics education reveals the importance of students' attitudes toward statistics on their statistics course outcome and their willingness to use statistics in the remainder of their degree program and in their future profession (e.g., Schau, 2003b; Ramirez, Schau &

Emmioglu, 2012). Therefore, teachers of statistics need to develop an engaging learning experience and model the relevance of learning the subject matter to students' lives more broadly (Beck & Kosnik, 2014). For example, social sciences students need to realize the value of learning basic statistical skills for their academic success and for their professional development (Davis & Mirick, 2015; Lalayants, 2012; Murtonen, Olkinuora, Tynjälä & Lehtinen, 2008; Parke, 2008). To achieve this goal, statistical ideas should be taught within the context of data (Gal, 2002; Shaughnessy, 2007; Watson, 2006) to illustrate the relevance of learning statistics (e.g., Hampden-Thompson & Sundaram, 2013; Parke, 2008; Rumsey, 2002).

In addition to learning how to produce quantitative information, students need to learn how to evaluate, judge and criticize the statistical information that they will encounter in research findings, and later in their field of employment (Gal, 2002; Parke, 2008; Rumsey, 2002). Thus, a discipline-specific approach to teaching statistical ideas to social sciences students (Davis & Mirick, 2015; Koh & Khairi Zawi, 2014; Lalayants, 2012; Murtonen & Lehtinen, 2003; Slootmaeckers, et al., 2014) may shift their attitudes toward learning statistical methods from a category of "things that are hard for me to learn" to a category of "things that help me understand research" (Murtonen, 2005, p. 33).

1.3 Purpose of the Study

As an instructor of statistics—teaching undergraduate introductory statistics courses—my goals for my students are to have them become interested in learning statistics, to understand the value (usefulness, relevance, and worth) of the subject in their personal and professional lives, and for them to feel capable of doing statistics. Therefore, I always strive to learn about my students' views toward statistics in order to make appropriate changes to the ways I deliver the course, and to make the learning of statistics more meaningful to them.

Through an examination of the literature in the field of statistics education, I learned about a theoretical framework that has been used to study students' attitudes toward statistics in various disciplines (Schau, 2003b). This theoretical framework can be used to understand students' affect toward, competence in, valuing of, perception of the difficulty of, interest in, and effort to learn statistics. Moreover, these attitudinal components can be used to study the changes in students' attitudes toward statistics from the beginning to the end of an introductory statistics course, as well as to investigate the interrelationships between them. Furthermore, with this theoretical framework, instructors of statistics or researchers can examine the interrelationships among students' attitudes toward statistics, their previous achievement in mathematics, and their statistics outcomes.

I became interested in using the same theoretical framework as the one described above for studying my students' attitudes toward statistics, particularly those students in the social sciences programs. Through my teaching experience, it has become apparent to me that students in the humanities and social sciences programs tend to experience more difficulties with learning statistics than those students who are in the sciences programs. As mentioned in the previous section, their difficulties may be attributed to their previous related experiences or achievements in mathematics, or to their current statistics course if it lacks relevant context-based examples from the social sciences to illustrate statistical concepts. As a result, students can become uninterested in learning statistical ideas or in using the subject after they leave their statistics course (e.g., in the remainder of their degree program and when employed).

In the summer of 2016, the Department of Computer and Mathematical Sciences at a large urban university offered a new course titled "Introduction to Statistics for the Social Sciences" to students enrolled in the Social Sciences programs. I was the instructor for this course. The social sciences faculties were interested in making the teaching and learning of statistics relevant for social sciences students so that students could become competent in understanding, interpreting and communicating statistical information presented in the field of social sciences. Therefore, I used relevant examples from the field of social sciences to illustrate statistical ideas and to keep students motivated and interested in learning statistics.

This new introductory statistics course for the social sciences provided me with the opportunity to conduct my current study. The purpose of my study was three-fold. First, I assessed how undergraduate social sciences students' attitudes toward statistics changed from the beginning to the end of their introductory statistics course. Second, I examined the relationship between students' attitudes toward statistics and their past mathematics achievement, their statistics course grade, their sex, and their year of study. Third, I investigated the interrelationships among social sciences students' attitudes toward statistics at the end of their course, their past mathematics achievement, and their statistics outcomes.

1.3.1 The Social Sciences Introductory Statistics Course

In the Introduction to Statistics for the Social Sciences course, there was less emphasis on formulas and calculations than in traditional introductory statistics courses. Instead, students were guided to make meaning of statistical summaries and graphical displays using either a web-based Survey Documentation Analysis (SDA) or PSPP, a free statistical software. The examples used to explain statistical concepts were from real data sets, which are available on the Internet (e.g., the General Social Survey and the Organisation for the Economic Co-operation and Development). The duration of the course was twelve weeks. Each week, there was a two-hour lecture session, which was taught by one instructor. There was a one-hour weekly tutorial session, which started in the second week of the course. There were three tutorial sections and each section was led by a different teaching assistant assigned to the course. In the lectures, statistical concepts were introduced within social-sciences contexts. In the tutorials, students discussed practice problems from the previous week's lectures, and completed a worksheet in small groups.

Students were often required to conduct a statistical analysis using either SDA or PSPP software for an assigned exercise and were asked to bring their statistical output to their tutorial for group discussions. Instructions regarding how to obtain these statistical outputs were provided to students in text and video formats. For additional help with the course contents and tutorial preparations, the course instructor and the teaching assistants provided weekly office hours. At the end of each tutorial, a short quiz was given to students based on the previous week's course content. Two of the tutorial times were scheduled in the lab. Students in the labs practiced how to extract real data from the Internet, import data into PSPP, and explore data using basic statistical analysis. In the labs, students received a worksheet to answer questions related to the data that they explored using PSPP.

A component of the course was to Read and Reflect on an article from social sciences that used at least one statistical method in the paper. Students were required to work in groups of three to five members to reflect on their selected article's statistical messages. This aspect of the course design was based on Gal's (2002) model for developing adults' statistical literacy. In his model, he lists ten worrying questions that adults should consider when they encounter statistical messages. The Read and Reflect project consisted of seven components to consider. The first five components required students to discuss their study's data collection and to summarize statistics and graphical displays. Students were instructed to evaluate any distorted patterns, missing information, or unusual observations they encountered while reading their chosen article. They were also asked to reflect on the ways in which the statistical information was checked for its validity. The last two components of the Read and Reflect project required students to reflect on the selected statistical methodologies of their chosen study and to propose additional statistical methods that they learned in the course that could answer the same research questions in their article. To expand the scope of their selected topic, students were asked to propose a new research question and a statistical method that would answer their research question.

The Read and Reflect project was a semester-long course project with opportunities for students to receive feedback from the instructor and the teaching assistants in the course. The project was assessed both by the course instructor and the students themselves. Students assessed the quality of their own work and the peers in their group.

The course had a midterm test and a cumulative final exam, both of which were based on multiple-choice questions. A model test and exam were provided to students for practice purposes to alleviate any test anxiety, whether due to format (multiple-choice questions) or because of general concerns. Students were permitted to bring hand-written aid sheet(s), one to the test and two to the final exam. They could write on both sides of the aid sheet(s).

In addition to the course instructor and teaching assistants' office hours, students could visit the Mathematics and Statistics Learning Centre (MLSC) and meet with a tutor to review course contents. The MSLC at the participating university offers free in-person and virtual tutoring to students taking any introductory and intermediate mathematics or statistics courses. The course also had the support of another program at the participating university, a peer-facilitated study group, which offered free weekly study sessions to the students.

1.4 Research Questions

The Introduction to Statistics for the Social Sciences course aimed at equipping undergraduate social sciences students with basic statistical skills so that they could understand the results of quantitative studies in the field of social sciences (e.g., in their course readings). Therefore, the elements of the course were designed in accordance with the academic focus of social sciences students. For instance, the lecture notes used real data sets from the General Social Survey and the Organisation for the Economic Co-operation and Development to show the relevance of statistical ideas in the field of social sciences.

Additionally, a course group project was included in the course, which was to read and reflect on an article from the field of social sciences that used basic statistical methodologies to conduct research. The project aimed at giving social sciences students the opportunity to collaborate with their peers, and to realize the value (usefulness, relevance, and worth) of statistics in their field, to feel capable of interpreting the statistical findings presented in their chosen article, and to become interested in learning statistics. The tutorial sessions in the course also reviewed statistical problems from the field of social sciences and provided students with opportunities to discuss the ways in which statistics are applied in their field.

Overall, the aspects of the course described above aimed at making the learning of statistics meaningful for the undergraduate social sciences students. As a result of the additional components included in this course, I became interested in examining the undergraduate social sciences students' attitudes toward statistics in the Introduction to Statistics for the Social Science course. In the current study, I investigated the following questions regarding undergraduate social sciences students' attitudes toward statistics:

1. How do undergraduate social sciences students' attitudes toward statistics change from the beginning to the end of an introductory statistics course for the social sciences?
2. How do undergraduate social sciences students' past mathematics achievements, their statistics course grade, their sex, and their year of study contribute to their attitudes toward statistics?
3. What are the structural interrelationships among undergraduate social sciences students' past mathematics achievements, their statistics attitudes at the end of the course, and their statistics outcomes?

1.5 Significance of the Study

It has long been an interest of researchers and educators in the field of statistics education to revamp introductory statistics courses and to deliver them in meaningful ways to those students who have difficulties with learning statistical content (e.g., Carnell, 2008; Dempster & McCorry, 2009; Garfield & Ben-Zvi, 2008; Murtonen & Lehtinen, 2003). Although studies that used a student-centred approach (Garfield, 1995) to teaching statistics showed positive results in students' course outcome and appreciation of learning statistics (e.g., Carnell, 2008; Parke, 2008; Ramirez-Faghih, 2012; Smith, 1998; Sovak, 2010), students' difficulties in learning statistical content for those in the humanities and social sciences programs remain present (e.g., Malik, 2015; Murtonen et al., 2008).

This study will inform both my future teaching of introductory courses in statistics for social sciences students and departments who offer introductory statistics service courses at the tertiary level in making appropriate revisions to the delivery of these courses. For example, instructors of statistics should consider students' lack of adequate prior mathematical or statistical knowledge and their low confidence in doing statistics. Therefore, extra support should be offered by departments to fill the gap in students' prior mathematical and statistical knowledge in order to strengthen students' confidence in doing statistics in their academic and professional life.

1.6 Background of the Researcher

I have always loved teaching, particularly teaching mathematics and arts. In elementary school, I modeled my teachers for my younger cousins and would show them what I had just learned at school. In my senior elementary grades, my aunt, who was an elementary school teacher, let me read her students' mathematics worksheets and write feedback on their papers. I really enjoyed helping my aunt. I asked her if I could visit her class at the earliest opportunity and be her teaching assistant for a day. In grade nine, I finally had the opportunity to visit my aunt's class. When my aunt stepped into her classroom, I was amazed at how students welcomed and interacted with her. It was evident that my favourite aunt was loved by her students. Her classroom environment was friendly and comfortable. I was certain that learning could happen in her classroom. My aunt is my very first model of a caring teacher.

I have always enjoyed doing mathematics. Alongside mathematics, I have always had an interest in the arts, because I watched my mother, who is an artist, work on art projects. She used creative approaches to help me understand concepts in elementary mathematics. For example, with her help, I learned the multiplication timetables using colours. It was really fun to see mathematics in a colourful and harmonious way. This way of seeing mathematics, as a fun subject, is what I wish for my students to experience.

In high school, I tutored my peers in their mathematics courses. It was a rewarding experience to see them happy. Therefore, teaching mathematics courses became my ultimate career goal. In my undergraduate studies at the University of Toronto, I initially enrolled in business studies, psychology, and visual arts programs. As part of my psychology degree requirement, I had to take an introductory statistics course. In that statistics course, I felt right at home. Statistics incorporates all of my interests: mathematics, arts, and psychology. I can work with data that has a context (e.g., in education) and explore data using multiple mathematical tools. This approach to problem solving, analyzing data, is much like doing a painting using various tools, colors and techniques insofar as both processes convey an idea and tell a story.

I attended all office hours offered by my statistics professors and their teaching assistants. I realized that studying statistics with the peers who also came to these office hours was essential to becoming successful. During office hours, we discussed statistical problems with a smaller number of students than in class. From these small-group discussions, I learned short cuts and easy tricks to solve statistical problems. Those experiences—working on problems with my peers—created a new level of self-confidence when engaged in problem solving. Working with my peers offered me a greater sense of preparation for test and exam times.

The professor of my introductory statistics course learned that I enjoy teaching my peers. She hired me as her teaching assistant after I completed two statistics courses. I decided to major in statistics and keep psychology as my other major. Additionally, I continued to take visual arts courses.

As a teaching assistant in statistics, I worked closely with students. I was thus able to identify students' challenges and misconceptions. Mostly, they lacked an appropriate mathematical foundation. For example, they struggled with doing algebraic calculations. I often heard from them about how much they feared taking a mathematically-oriented course, and that they were not math people. The concerns they expressed to me explained why they left taking a statistics course until their final year of studies. Therefore, for some students, there was a gap of a few years since their last mathematics course. It became apparent to me that the subject that I enjoyed was not my students' favourite. Their aim was just to complete the statistics course as part of their degree requirements.

Students' challenges became my own teaching challenges. Over the years of teaching the same introductory statistics course, I realized that students' difficulties and struggles are quite common among those in the humanities and social sciences programs. I realized that it is necessary to offer extra resources to these students so that they become successful. For example, I provided handouts in my tutorials, which explained step-by-step procedures for how students need to solve statistical problems.

I mainly covered the big statistical ideas of the course in order to prepare my students for the tests and the exams. However, I wanted students to be more engaged with the learning of statistical content. A small breakthrough happened during my third year of appointment as a teaching assistant. In the first tutorial of that semester, I showed students how to collect data. I distributed a little survey that asked students to indicate their program and year of study. After collecting the student survey, with the help of these students, we analyzed the data in class. We explored frequency distributions for students' program and their year of study. We also explored bivariate associations between students' program and their year of study. I noticed a shift in the class atmosphere. Students began asking "what if" questions. For example, they asked how they should show the distribution of students' program and their year of study when considering information such as students' gender. At that moment, I realized that moving away from the textbook and bringing in relevant examples to the class can engage students with learning statistical content at a deeper level.

In my last year of undergraduate studies, I had the opportunity to work on a research project with my undergraduate supervisor in psychology. The project was about understanding the effects of media images on perceptions of disability. I recruited participants and collected quantitative data on perceptions of disability. I was happy that I could employ some of the statistical tools that I had learned in my statistics courses for analyzing my own data. I have shared this experience with my students. Those students in the psychology program especially appreciated learning about how statistics can be applied in their chosen field.

My passion for teaching and learning statistics encouraged me to pursue a master's degree in statistics. During my master's studies, I continued working as a statistics course teaching assistant. Due to the recurring struggles that my students faced while taking an introductory statistics course, I became motivated to pursue doctoral study in this area at the Ontario Institute for Studies in Education (OISE).

In the first semester of my PhD studies at OISE, I realized that transitioning from a purely quantitative field of study (e.g., statistics) to a doctoral study in education is challenging. Although I was very excited to take courses in education, I could not clearly articulate the purpose of my research study to my professors and peers. I knew, however, that it is meant for me to be at OISE and that my PhD journey will be meaningful.

On an emotionally-charged day, as I was deeply thinking about whether or not I should continue with my PhD studies, I sat on one of the benches outside of the OISE building. It was a cold day in winter, but the sun was out. I looked at the OISE building and asked the universe, why have I really arrived here? What can I contribute to the field of education? I saw the sun, suddenly, shinning so ever-brightly on another bench, across my direction. I walked toward the bench to look – I believed that would a sign. The sun was shining on a dedicated plaque, which stated: “In proud memory of J. Roby Kidd and Margaret Easto Kidd, fierce advocators of public education and lifelong learning”. These words really moved me and encouraged me to think positively about my journey. I felt so privileged reading these words and learning about this special bench. I also became interested to learn about these two educators. I learned that Dr. Roby Kidd’s work was in the field of adult education and that Dr. Margaret Easto Kidd’s work was in the field of early childhood education. I have sat on this very special bench throughout my PhD studies and have reflected on my challenges and the encouragements that I have received from my supervisor, Dr. Doug McDougall.

My graduate studies at OISE have provided me with opportunities to read, reflect on, and examine the current research in mathematics and statistics education. Additionally, in my graduate studies, I had an opportunity to work as a research assistant on a project that aimed to investigate the effects of an inverted classroom on undergraduate students’ attitudes toward statistics in an introductory course. In that role, I learned about the current research in statistics education and a widely-used attitudes survey, Survey of Attitudes Toward Statistics, SATS-36©. I learned how to recruit participants for collecting data, and how to analyze the survey data regarding students’ attitudes toward statistics.

I have recently transitioned to a new role as a sole course instructor teaching introductory courses to undergraduate students. I really enjoy my new appointment. I learned that I have to carefully plan my lessons and think about the most logical ways to deliver statistical content in my lectures. I realize that I need to teach content at a slow pace because of the challenges my students face, and provide them with lots of relevant examples and resources. For example, I provide voiceover videos of my lecture notes so that those who need to re-visit the course materials can have unlimited access to review this content. I feel so privileged to have learned about the current exemplary teaching practices in mathematics and statistics education.

1.7 Limitations of the Study

This study assessed undergraduate social sciences students' attitudes toward statistics in an introductory statistics course designed for social sciences students at a certain university. The current study was conducted in one classroom. Therefore, the findings may not be generalizable for all students who take an introductory statistics course at the undergraduate level.

However, the findings of this study might be generalized for those students in the social sciences programs who exhibit similar characteristics to the ones described in the current study. Therefore, students and instructors in other introductory statistics courses for non-major mathematics students may learn from this study.

The course under study was taught by one instructor. Therefore, students' attitudes might be influenced by the instructional style of the course instructor. Moreover, the course instructor was the researcher of the current study. Although the data for the current study was collected and de-identified by a research assistant with no connection to the course and evaluation of the students in the course, students in the course under study were aware that their course instructor was conducting a research study in their course. Therefore, the findings from the current study should be interpreted with caution.

The participants in the current study were asked to provide feedback regarding their attitudes toward statistics and their perception of their previous achievement in mathematics. Thus, a self-selection bias may exist. It is possible that those students who tend to be high or low achievers participated in this study.

Lastly, it was the goal of the current study to include in its data collection and analyses both students' achievement in their last high school mathematics course and their perception of their past mathematics achievement. However, after consulting with the participating university's Office of the Registrar, it was found that many students did not complete a senior-level high school mathematics course. The participants in the current study were in social sciences programs, and did not need to complete a senior-level high school mathematics course in order to be admitted into their program of study at the participating university. Therefore, for the current study's statistical analyses, the component of past mathematics achievement only refers to the participants' self-reports of their past mathematics achievement.

1.8 Plan of the Thesis

This thesis is compromised of five chapters. Chapter One provides an overview of my study including the research context, purpose of the study, research questions, significance of the study, my background as the researcher, and limitations of the study. Chapter Two contains the literature review for my thesis. Within this section, I first describe the emergence of the field of statistics education, and the three domains of statistical literacy, reasoning, and thinking. I then describe a model of teaching statistics that encourages the use of statistical-talks in the classroom. I also describe the benefits of a contextual approach to teaching statistics.

After providing the background of the emergence of statistics education as a field, I describe the research on the importance of studying attitudes toward statistics. Next, I describe Eccles and colleagues' application of the expectancy-value theory of achievement motivation to mathematics education (Eccles et al., 1983), which provided the foundation for the conceptual structure of Statistics Attitudes-Outcomes Model (Emmioglu, 2011). I conclude Chapter Two by providing a summary of previous studies that used the application of Eccles et al.'s (1983) expectancy-value theory of achievement motivation to mathematics education for studying students' attitudes toward statistics.

Chapter Three describes the research methodology and instruments that I use in my study. Within this section, I describe the overview of the new introductory statistics course that is designed for the social sciences students, research design, participants for my study, procedure and data collection, data analysis, and ethical considerations.

Chapter Four presents the findings for the current study. Within this section, I discuss data screening and checking the assumptions for conducting the present study's statistical analyses. I provide descriptive statistics and correlation analyses for both pre-test and post-test responses to SATS36©. I discuss the relationships between students' attitudes toward statistics from the beginning to the end of their introductory statistics course with their past mathematics achievement, their statistics course grade, their sex, and their year of study. In addition, I describe the results of the path analysis for investigating the interrelationships among social sciences students' past mathematics achievement, their statistics attitudes by the end of the course, and their statistics outcomes. I conclude Chapter Four by providing a summary of the results of the current study.

In Chapter Five, I discuss how the findings of the current study are in line with the findings from the existing literature and how the results of the current study supported the theoretical framework of the expected-value theory model (Eccles et al., 1983) and the conceptual structure of Statistics Attitudes-Outcomes Model (Emmioglu, 2011). I conclude Chapter Five by describing the implications of my study for future research and practice of statistics education. I offer recommendations to departments at the tertiary level who deliver introductory service courses to social sciences students.

Chapter Two: Literature Review

2.1 Introduction

In this chapter, I describe the emergence of the field of statistics education, the three statistical domains, statistical-talks, and the role of context in learning statistics. I then describe students' attitudes toward statistics, the expected-value theory, and its role in understanding students' attitudes toward statistics.

I begin the chapter by describing the emergence of the field of statistics education, and how the 1980s reform movement in mathematics education, which encouraged the use of contexts (e.g., data) in teaching mathematics, presented the case for teaching statistics through the use of contexts. Additionally, I describe how the Quantitative Literacy Project shaped the importance of teaching statistics by including statistical content into mathematics curricula. Afterwards, I outline the three statistical domains of: statistical literacy, reasoning and thinking—which are described in statistics education as essential learning goals for an introductory statistics course. I describe how the encouraging of statistical-talks in a contextual approach to teaching statistics for the social sciences students fosters the learning of statistical ideas. In addition, I draw on the social constructivism theory of learning in mathematics education, and discuss how it can facilitate statistical-talks and a contextual approach to teaching statistics.

After providing the background to the field of statistics education, I describe attitudes toward statistics, and factors that have been reported in statistics education that contribute to understanding attitudes about statistics. Next, I describe the expected-value theory, which is the foundation for the conceptual structure of Statistics Attitudes-Outcomes Model. I then provide summaries of previous studies that used Statistics Attitudes-Outcomes Model as their theoretical framework to examine students' attitudes toward statistics.

2.2 Statistics Education

In the 1960s, an interest emerged in mathematics education in teaching students at all grades and tertiary levels how to use and analyze data (Garfield, & Ben-Zvi, 2008). In 1967, a joint committee was formed between the American Statistical Association (ASA) and the National Council of Teachers of Mathematics (NCTM), which focused on designing curricula for teaching statistics and probability in grades K-12 (Garfield, & Ben-Zvi, 2008). In the 1970s, many instructional strategies were introduced in mathematics education that aimed at the development of students' statistical thinking in meaningful ways (Garfield, & Ben-Zvi, 2008). In the 1980's, the reform movement in mathematics education challenged traditional approaches to teaching mathematics by incorporating relevant real-life problems that emphasized the place of contexts to explain mathematical concepts (Moore, 1997). The reform in mathematics education created what Moore (1997) refers to as "The Case of Statistics" (p. 124). Since statistics relies on the exploration of real-life data, the teaching and learning of statistics gained strength in mathematics education (Garfield, & Ben-Zvi, 2008).

In their influential document, *Curriculum and Evaluation Standards for School Mathematics,* NCTM (1989) included "Data Analysis and Probability" as one of the five content strands. This document and its revised version (NCTM, 2000), *Principle and Standards for School Mathematics*, became the foundation for reform in mathematics curricula. The "Data Analysis and Probability" content standard in NCTM (2000) describes the necessary statistical tools and skills that students should possess by the end of their high school years. For example, students need to be able to discuss the shape, centre, and spread of a distribution (NCTM, 2000).

These skills are essential for the critical evaluation of statistical claims and for being an informed citizen (Gal, 2002). Likewise, Steen (2001) asserts in his book, *Mathematics and Democracy: The Case for Quantitative Literacy,* that these skills give people "tools to think for themselves, to ask intelligent questions of experts, and to confront authority confidently. These are the skills to survive in [the] modern world" (p. 2).

The Guidelines for Assessment and Instruction in Statistics Education (GAISE, 2005) complements NCTM's (2000) recommendation for developing informed and quantitatively literate citizens, asserting: "[e]very high school graduate should be able to use sound statistical reasoning to intelligently cope with the requirements of citizenship, employment, and family and to be prepared for a healthy, happy, and productive life" (p. 1). Statistically literate adults will know "how to interpret the data in the morning newspaper and will ask the right questions about statistical claims" (GAISE, 2005, p. 3).

The Quantitative Literacy Project (QLP) was a collaboration between ASA and NCTM led by Richard Scheaffer in the 1990s, and influenced the teaching and learning of statistics (Garfield, & Ben-Zvi, 2008). Steen (2000) describes quantitative literacy as something "that sits halfway in between [mathematics and statistics], sharing aspects of both but contributing elements that are distinctively its own" (p. 1). He adds that quantitative literacy "involves mathematics acting in the world" (p. 6); "[it] is not really science at all; it is more a habit of mind, an approach to problems that employs and enhances both statistics (the science of data) and mathematics (the science of patterns)" (p. 3).

For mathematics to be meaningful to those learning it, Steen (2000) argues that mathematics needs to use authentic contexts that interest and engage students. As Moore (1998) puts it: "working with data gives a context to mathematics exercises that would otherwise be abstract and is a rich setting for problem-solving and group work" (p. 1255). In the 1990's, Richard Schaeffer created "Data analysis and Probability" activities for middle and high school students (Garfield, & Ben-Zvi, 2008). These activities provided guidance for students to explore data within real-life contexts, and many instructors have found them relevant for explaining statistical ideas and motivating students (Garfield, & Ben-Zvi, 2008).

It is imperative for students to realize the difference between the subjects of mathematics and statistics (delMas, 2004). It should be made explicit to students that: "mathematics is imbedded in statistics and statistics is an ideal field to provide meaningful context for the learning of many mathematics concepts" (Gattuso, 2006, p. 5). Furthermore, students in statistics courses should learn to distinguish between observational studies and experimental designs, as these are core statistical ideas, which differentiate statistics as a subject from mathematics (Moore, 1997).

Although calculations and formulas play an important role in students' mathematical competencies, they should not be the central focus in teaching and learning introductory statistics (Moore, 1997). Since there are many readily available statistical softwares that can handle heavy calculations, the teaching and learning of statistics should rely on technology for exploring data and developing a conceptual understanding of statistics (GAISE, 2016; Moore, 1997; Utts, 2003). As Rumsey (2002) points out, "formulas are not part of students' everyday language, but explaining how to do something in words can be a useful life skill" (p. 6). DelMas (2002) echoes Rumsey's (2002) promotion of a kind of statistical understanding for students that emphasizes "how" to obtain statistics from data, in addition to the questions of "why" the statistics are necessary to obtain, and "what" is the purpose for obtaining them. Thus, instead of emphasizing the mechanical procedure of conveying statistical ideas, instructional methods should focus on students' decision-making, which is essential for the development of their mindset in problem solving (Rumsey, 2002).

2.2.1 The Three Statistical Domains of an Introductory Statistics course

Prior to the reform in mathematics education, teaching an introductory statistics course focused on skills, procedures, and computation, which do not develop students' statistical competency (Rumsey, 2002). Recently, those teaching introductory statistics courses have recognized the importance of developing three domains: statistical literacy, statistical reasoning, and statistical thinking (Garfield & Ben-Zvi, 2008). However, the degree to which introductory statistics courses focus on these three domains vary across disciplines. I will next describe each of these domains.

2.2.1.1 Statistical Literacy

Statistical literacy is an overarching goal for the development of statistical competencies, while it also serves as a foundation for statistical reasoning and thinking (Gal, 2002; Rumsey, 2002). Teaching for statistical literacy involves promoting an informed citizenry with developed scientific research skills (Reston, 2007; Rumsey, 2002). Ben-Zvi and Garfield (2004) add that these skills mean: "being able to organize data, construct and display tables, and work with different representations of data" (p. 7). The GAISE (2005) College Report defines statistical literacy as "understanding the basic language of statistics (e.g., knowing what statistical terms and symbols mean and being able to read statistical graphs) and fundamental ideas of statistics" (p. 14).

Statistical literacy involves "an *appreciation* of statistics, which can only come from a person's psychological mindset or disposition" (Bond, Perkins & Ramirez, 2012, p. 7). Both cognitive (understanding) and affective (attitudes and beliefs) areas are needed to develop statistical literacy (Bond et al., 2012; Watson & Callingham, 2003). Watson (1997) asserted that statistical literacy involves a three-tiered hierarchy of skills: basic understanding of statistics, an understanding of statistics based on context, and an inquisitive attitude.

Similarly, Gal (2002) proposed a model for the development of adults' statistical literacy, involving two context-dependent elements. The first is the knowledge element, with five components: literacy skills, statistical knowledge base, mathematical knowledge, context knowledge, and critical questioning. The knowledge element is concerned with people's ability to interpret, criticize statistical information, and make data-based arguments. The second element is dispositional elements, with two components: beliefs and attitudes, and critical stance. The dispositional element is concerned with the ways in which people react to statistical information and share and communicate their opinions about statistical issues. These two context-dependent elements in Gal's (2002) model aim at making adults capable of reading, understanding, and criticizing statistical information embedded in texts or presented via tabular and graphical displays. Moreover, with basic statistical skills, adults will be able to manage a set of data, use appropriate statistical methods to analyze data, and use appropriate statistical terminologies to interpret data (Gal, 2002; Koh & Khairi, 2014).

2.2.1.2 Statistical Reasoning

Statistical reasoning emphasizes cognitive domains, meaning individual's active engagement and reasoning with the data such as interpreting graphs and summary statistics (delMas, 2002). Ben-Zvi and Garfield (2004) defined statistical reasoning as: "the way people reason with statistical ideas and make sense of statistical information" (p. 7). This definition suggests that developing statistical reasoning is not independent of statistical literacy. One would need to be statistically literate in order to demonstrate statistical reasoning (Bond et al., 2012).

Garfield (2002) lists six reasoning goals that students should achieve: 1) reasoning about data, 2) reasoning about the representation of data, 3) reasoning about statistical measure, 4) reasoning about uncertainty, 5) reasoning about sample, 6) reasoning about associations. Statistical courses, therefore, need to include activities that can engage students with real-life data to develop their deeper understanding of the abstract concepts needed to reason about data, and the best way to visualize statistical information and relationships (delMas, 2004; GAISE, 2016; Garfield, 2002; NCTM, 2000).

2.2.1.3 Statistical Thinking

Statistical thinking is concerned with developing habits of mind to solve statistical problems (Chance, 2002). This means thinking beyond the data and considering variables not included in the study that might contribute to understanding the variability and pattern of data (Chance 2002; Garfield & Ben-Zvi, 2005). This type of thinking pushes for the interplay between statistics and the context of data in order to arrive at meaning (Wild & Pfannkuch, 1999). Those who understand the context of data can provide explanations to the source of variations in the data (Watson, 2006). Understanding the variability in the data enables modeling the variation, selecting appropriate statistical tests and analyses, checking assumptions for the validity of statistical measures, and drawing conclusions (Ben-Zvi & Garfield, 2004; Chance, 2002; GAISE, 2016; Moore, 1997).

Furthermore, thinking statistically allows those who are grappling with data to identify the limitations of statistical methods, as well as issues with the design of a study and the collected data (Chance, 2002). Although statistical thinking could be viewed as a statistician's behavior when working with data, this cognitive domain can be developed and improved by gaining more statistical knowledge (Wild & Pfannkuch, 1999).

DelMas (2002) illustrated in a Venn diagram (Figure 1) that, if the focus of instruction in an introductory statistics course is on the development of statistical literacy, then maturation of statistical reasoning and thinking will depend on the fostering of this statistical literacy. This perspective promotes statistically competent and literate individuals (Rumsey, 2002).

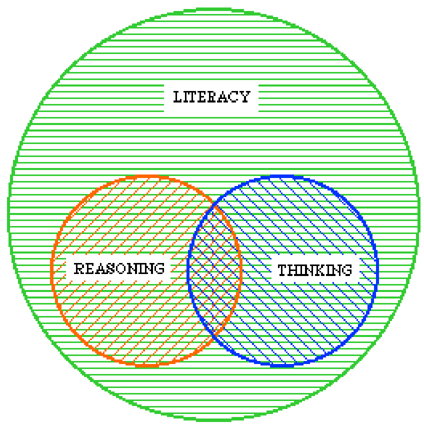

Figure 1. Statistical Reasoning and Thinking within Statistical Literacy (delMas, 2002)

2.2.2 Mathematical Background Knowledge for an Introductory Statistics Course

A basic knowledge of operations in numbers and algebraic manipulation skills is needed in order to succeed at developing statistical literacy, reasoning, and thinking in an introductory statistics course (Dempster & McCorry, 2009; Gal, 2002; Schau, 2003b). Since statistical learning is mainly concerned with reasoning about variability in data sets, students, therefore, need to be able to make sense of a set of numbers (e.g., data values) and realize how numbers differ from each other (Garfield & Ben-Zvi, 2005).

In their document *Principle and Standards for School Mathematics,* NCTM (2000) suggests that instructional programs should enable all students to develop number sense and algebraic manipulation skills. The document describes number sense as being able to understand and represent numbers, realize relationships among numbers, carry out computations, and reasonably estimate numbers. Furthermore, the document describes algebraic manipulation skills as being able to understand patterns, quantitative relations, and functions, and to represent and analyze mathematical models using algebraic symbols.

In an introductory statistics course, students need to know how to compute statistics such as proportions, means, medians, and standard deviations so that they can evaluate and judge the validity of statistical information (Gal, 2002). Garfield and Ahlgren (1998) claim that students' difficulties with grasping ideas of probability stem from their poor development of proportional reasoning and conceptions of rational numbers in their former mathematics courses. Furthermore, they argue that students' improvement of these skills is necessary before learning probabilistic and statistical reasoning.

Peck, Gould and Utts (n.d.) describe six mathematical topics and concepts that they consider to be necessary preparation for success in an introductory statistics course. These topics are: Numbers and Number Line, Operations on Numbers, Sets, Equations and Inequalities, Graphing Points and Lines in Two Dimensions, and Reading Tables and Graphs and Approximating Area. The authors provide examples of statistical topics in an introductory statistics course that they believe are dependent on the mastery of the associated mathematical topics that they list in their paper. In what follows, the authors' discussion of each of these topics is described.

The category of Numbers and Number Line is concerned with developing students' ability to find the distance between two points on the number line so that they can calculate deviations from the mean and calculate z-scores. The authors add that students should be able to round decimal points so that they can calculate numerical summary statistics, test statistics, and confidence intervals. Moreover, they note that students should be able to order decimal points so that they can calculate medians and quartiles, and compare *P*-values to a significance level. They also emphasize that students should be able to convert between fractions, decimals, and percentages so that they can calculate and interpret probabilities, margins of error and confidence intervals.

The category of Operations on Numbers is concerned with developing students' ability to perform signed number arithmetic so that they can calculate summary statistics, z-scores, residuals, test statistics, and confidence intervals. The authors add that students need to be able to use technology to calculate powers of a number and the square root of a number so that they can calculate the variance and standard deviation of a sample. Moreover, they explain that students should be able to understand the order operations in expressions and formulas so that they can calculate probabilities, test statistics, and confidence intervals.

The category of Set is concerned with developing students' understanding of Venn diagrams so that they can understand probability rules and calculations. The authors add that students need to be able to use set notation in order to define sample spaces and events. Furthermore, they suggest that students need to be able to find the complement of a set, and be able to find the union and the intersection of two sets so that they can define events and calculate their probabilities.

The category of Equations and Inequalities is concerned with developing students' ability to evaluate algebraic expressions in order to calculate summary statistics, z-scores, test statistics, confidence intervals, and regression coefficients. The authors add that students need to be able to solve a linear equation in one variable so that they can find percentiles for a normal distribution.

The category of Graphing Points and Lines in Two Dimensions is concerned with developing students' ability to plot an ordered pair (x, y) in a rectangular coordinate system so that they can create and understand scatterplots and residual plots. The authors add that students need to be able to draw the graph of the line based on the equation of the line so that they can graph the regression line. Moreover, they suggest that students need to be able to understand the slope of the line as the changes in y associated with a 1-unit change in x so that they can understand and interpret regression coefficients in a context of the data. The authors suggest that students need to be able to use the equation of a line to find the y-value associated with a given x-value in order to use the regression line to make predictions. Furthermore, they add that students need to be able to find the vertical distance between a point and a line so that they calculate residual points in data.

The category of Tables and Graphs and Approximating Areas is concerned with developing students' ability to extract information from tables and graphs in order to interpret graphical displays of data. Moreover, the authors explain that students need to be able to approximate the area of a shaded region based on the total area under a curve or a histogram in order to approximate probabilities and P-values.

The authors argue that students, who have forgotten or who are not fully equipped with the above-mentioned mathematical ideas, benefit from a mathematics preparatory course, which they referred to as an efficient pathway to statistics. They suggest that a preparatory mathematics course can be taken either prior to an introductory statistics course or simultaneously with the course. They add that a preparatory mathematics course that is offered simultaneously with an introductory statistics course should introduce these topics in the same order in which students learn topics in their statistics course.

The Principles of Mathematics course (academic or foundations) in the Ontario Curriculum, Grades 9 and 10 Mathematics, 2005, include topics such as the ones described by Peck et al. (n.d.), which can prepare students for an introductory course in statistics at the high school level (e.g., Grade 12 Mathematics of Data Management) or at the post-secondary level.

2.2.3 How Students Learn Statistical Ideas

Statistical ideas are best conveyed to students when they are accompanied with good examples (Moore, 1998) and when they connect to "students' personal interest and stimulate their motivations for numerical and quantitative studies" (Gattuso, 2006, p. 5). Moore (1997) claims: "the most effective learning take[s] place when content (what we want students to learn), pedagogy (what we do to help them learn), and technology reinforce each other in a balanced manner" (p. 124).

Adding to Moore's view, Utts (2003) argues that there needs to be less emphasis on calculations, and instead, more focus on understanding statistical messages. Furthermore, with readily available technological tools, "students can focus on decision-making, reflection, reasoning, and problem-solving" (NCTM, 2000, p. 24). For example, Parke (2008) describes how technology supported her students' exploration of data and understanding of the relationships and connections among statistical elements. In computer labs, Parke's students compared and discussed their statistical results across several data sets. They explored the influence of removing or retaining extremely low or high values on their statistical analysis. They learned that by removing extreme values from data, statistics such as estimated correlation and coefficient of determination would increase, and, in turn, estimated standard error would decrease.

2.2.3.1 Fostering Statistical-Talks

The GAISE (2005) College Report asserts that activities in an introductory statistics course should provide students with opportunities to: "learn from each other, understand important statistical ideas, practice communicating statistical language, and to discuss and think about the problem" (p. 18). As a pedagogical tool to encourage rich discussion around statistical concepts, Parke (2008) required her students to read and reflect on a published quantitative article in their own discipline. Her students were prompted to identify variables in their chosen article, evaluate authors' conclusions, critically question the credibility and significance of quantitative information by going beyond the data, and ask the authors something not included in their chosen study's discussion. Parke's approach is similar to what Gal (2002) refers to as taking a critical stance toward statistical information.

Parke (2008) repeatedly encouraged classroom discussions around statistical issues that she believes will prepare students with skills needed in their future careers (Hampden-Thompson & Sundaram, 2013; Murtonen et al., 2008; Rumsey, 2002). She explains that collaborative learning environments enable students to operate as practitioners who may need to interpret, understand, and communicate quantitative results to various audiences, for example: teachers, counselors, parents, administrators, students, community leaders, or policy makers. Thus, statistical-talks will support students in their capacity as researchers who need to conduct, analyze, and interpret their own data.

Parke's students were receptive to her instructional approach and appreciated the opportunity to be around their peers to "talk statistics". The language of statistics became more fluent to them. In addition, they commented that, while encountering different ways of interpreting results deepened their understanding of research questions, it also taught them how to effectively communicate results and how to improve the quality of their writing. Thus, Parke's instructional approach is what Beck and Kosnik (2014) refer to as a sound teaching vision, which focuses on building a sociable class community that fosters collaboration among students. Individual learning can be amplified through interactions with peers in collaborative learning environments (Beck & Kosnik, 2006). This strategy is consistent with the social-constructivist viewpoint in mathematics education.

2.2.3.2 Social Constructivism

Social constructivism tends to have a sociocultural emphasis, and is concerned with how participation in social interaction and culturally-oriented activities influences psychological development (Beck & Kosnik, 2006; Cobb, 1994; Vygotsky, 1978). Vygotsky (1978) claimed that "every function in the child's cultural development appears twice: first, on the social level, and later on the individual level; first between people…, then inside the child" (p. 57). Thus, Vygotsky's viewpoint assumes that "meaning originates in society and [is] transmitted via social interaction to children" (Thompson, 2013, p. 4).

Although Vygotsky's work emphasized how children come to being through their social interactions in society, the theory of social constructivism can also be applied to adults' learning, and specifically to adults' mathematical learning. Paul Ernest (1991) introduced the term social constructivism to mathematics education and built on Vygotsky's notion of enculturation into community of practice, focusing on the objectivity of adult mathematics.

> Social constructivism links subjective and objective knowledge in a cycle which contributes to the renewal of each other. In this cycle, the path followed by new mathematical knowledge is from subjective knowledge (the personal creation of an individual), via publication to objective knowledge (by intersubjective scrutiny, reformulation, and acceptance). Objective knowledge is internalized and reconstructed by individuals, during the learning of mathematics, to become individual's subjective knowledge, thereby completing the cycle. (Ernest, 1991, p. 43)

Social interactions among students with similar programs of study can better facilitate statistical learning (Parke, 2008). Communicating about their interests and values leads to more engagement and deep learning (Eccles et al., 1983; Linnenbrink & Pintrich, 2003). Moreover, the social dimension makes learning enjoyable. As Dewey (1938) pointed out: "education is essentially a social process. This process is realized in the degree in which individuals form a community group" (p. 58).

2.2.3.3 Context Approach to Teaching Statistics

The context approach to teaching statistics allows exploration of a variety of data familiar to the learners, and empowers students to recognize and understand wider social issues pertaining to their discipline of interest. As noted by Dewey (1910): "The data at hand cannot supply the solution, they can only suggest it" (p. 12). Thus, students need to explore statistical ideas within a given context. Gal (2002) asserts that the context-awareness of data is important for adults' development of statistical literacy. Rumsey (2002) supports Gal's view and asserts that statistical problems that are presented within contexts can encourage relevant questions for learners to investigate, a process that they may apply in their future workplace.

Shaughnessy (2007) and Shaughnessy, Garfield and Geer (1996) acknowledged the role of context in making sense of data, which they named "reading behind the data". The context-awareness of a problem will allow those who grapple with data to explain certain outcomes and patterns that emerge from data (Gal, 2002). Knowing the background of data will enable people to fully interpret the results and connect the evidence to the claims, and also permit them to go beyond the data, challenge and critically question statistical information (Gal, 2002; Makar & Rubin, 2009; Watson, 2006).

Beck and Kosnik (2014) discuss greater program integration in teaching practices. Topics for discussion in an applied statistics class need, therefore, to show how disciplines can be integrated in meaningful ways, and with use of multiple examples of how statistics is used in other fields. For example, to fully understand a lesson from social studies—a fair water allocation in Syria, Turkey, and Iraq—students in grade 7 learned to consider the amount of accessible water and the population in each country to calculate a per capita measure (Vahey et al., 2012). While students learned to make data-based arguments, they realized how statistics helps to explain a sociological concern (Vahey et al., 2012).

By emphasizing the value of integrating subjects to students, educators can achieve a holistic approach that fosters deeper understanding of subjects, and demonstrates their connections to each other (Beck, 2010). In that regard, students can see mathematics as a tool for looking at the world in a way that is applicable to their life (Horn, 2012). For example, Hampden-Thompson and Sundaram (2013) provided opportunities for students in education to explore and apply statistical ideas in their own field of study. 93% of students reported that statistical data analysis will be useful in their future orientation, and 70% reported that they were planning to do a research project that involves some statistical data analysis. Therefore, a context approach to teaching an introductory statistics course can be an effective approach to teaching statistics to social sciences students (Davis & Mirick, 2015; Lalayants, 2012). In this approach, we can foster teaching statistics for deep understanding and develop appreciation (e.g., positive attitudes) of statistics for adult learners who need to acquire basic statistical knowledge for their academic, personal and professional lives (Bond et al., 2012; Davis & Mirick, 2015; Gal, 2002; Parke, 2008; Rumsey, 2002).

2.3 Attitudes Toward Statistics

Attitudes toward statistics can be described as the "summation of emotions and feelings experienced over time in the extent of learning statistics" (Gal et al., 1997, p. 5). Researchers claim that students' attitudes and beliefs influence the teaching and learning of statistics, and will also influence students' perception of statistical messages after they leave a statistics course (e.g., Gal et al., 1997; Ramirez et al., 2012; Schau, 2003b).

Attitudes toward statistics can be contextualized as a multidimensional concept that includes affective, cognitive, and behavioural dimensions (Olson & Zanna, 1993). It can be further defined as a disposition to respond positively or negatively to all objects, situations, or people related to statistical learning (Gal et al., 1997; Schau, 2003b). Gal (2002) distinguishes between the definitions of attitudes and beliefs. He claims: "attitudes are relatively stable, intense feelings that develop through gradual internalization of repeated positive or negative emotional responses over time" (p. 18). Although like attitudes, "beliefs take time to develop" (Gal, 2002, p. 18), they are "less emotionally intense than attitudes, and are stable and quite resistant to change compared to attitudes" (Gal, 2002, p. 19).

Gal (2002) asserts, "certain beliefs and attitudes underline people's critical stance and willingness to invest mental effort or occasionally take risks as part of acts of statistical literacy" (p. 18). Positive attitudes toward statistics lead to having appreciation and value for the contents being taught (Schau, 2003b; Wise, 1985). For example, students who have positive views toward statistics will understand the relevance of learning statistics and will be more likely to carry out statistical inquiries in their future academic and professional developments (Davis & Mirick, 2015; Slootmaeckers et al., 2014). However, poor attitudes toward statistics can create barriers for learners in grasping statistical concepts (Lalayants, 2012; Shaughnessy, 1992). For example, it may affect learners' development of statistical literacy and thinking skills (Davis & Mirick, 2015; Gal et al., 1997). The National Council of Teachers of Mathematics has recommended that instructional methods and assessments pay attention to students' attitudes toward mathematical subjects (NCTM, 1989, 2000).

Studies about students' attitudes toward statistics primarily stem from students' prior experiences in mathematics, their mathematics ability beliefs, their expectation for success in mathematics, and the degree to which they reflect on the usefulness, importance, and interest in doing mathematics (Wigfield, & Eccles, 2000). Next, I describe the expected-value theory (Eccles et al., 1983) that formed the basis for understanding students' attitudes toward statistics.

2.4 Expectancy-Value Theory

The concept of expectancy for success originates from the work of motivation and achievement theorists (e.g., Atkinson, 1957; Bandura, 1977). This concept describes "individual differences in the motives to achieve and the effects of subjective expectancy on both this motive and the incentive value of success" (Eccles et al., 1983, p. 79). Atkinson (1957) defines expectancy as "a cognitive anticipation… that performance of some act will be followed by a particular consequence" (p. 360). He adds that the strength of expectancy can be presented as "subjective probability of the consequence of the given act" (p. 360). Furthermore, he defines value as "the relative attractiveness of a specific goal that is offered in a situation… as a consequence of some act" (p. 360).

Eccles and her colleagues (Eccles et al., 1983; Eccles & Wigfield, 2002) posited that students' beliefs in regards to how they will perform on a task, defined as expectancies for success, are related to four components of subjective task value: interest-enjoyment value, attainment value, utility value, and relative cost. Interest-enjoyment value refers to the immediate enjoyment one gains from engaging in a task. Attainment value refers to the importance one places on doing well in the task. Utility value refers to how useful a task is to a person's future goal. Finally, relative cost refers to assessing how much effort is needed to succeed, and the cost of that in terms of loss of engagement in other activities. Eccles and colleagues posited that students are more likely to choose to engage in and do well on tasks that they value and expect to do well in.

Eccles et al.'s (1983) expectancy-value model was first applied to studying mathematics engagement and achievement and the role of gender differences among grades 1 and 2 schoolchildren. Their model theorizes that students' expectancy for success and subjective task value directly influences their achievement-related choices, and also influences their performance, effort, and persistence (Eccles et al., 1983; Eccles & Wigfield, 2002). Their model assumes that expectancies for success and value are influenced by several factors. These factors include: self-schemata, achievement goals, self-conception regarding one's ability (e.g., successfully doing a mathematical task), one's perception of the difficulty of a task (e.g., perception of the demand of a mathematical task), and one's perception of the value of a task (e.g., learning mathematics for everyday life and future work demands). Furthermore, one's affective memories (e.g., perceptions of past achievement-related experiences when working on similar tasks) are also assumed to influence these factors.

Schau et al. (1995) used Eccles et al.'s (1983) expectancy-value model of behaviour in mathematics achievement as a general framework for designing the conceptual structure of Student's Attitudes Toward Statistics – Model (SATS-M). In the next section, I describe the SATS-M and how it is congruent with Eccles et al.'s (1983) expectancy-value model.

2.5 Students' Attitudes Toward Statistics – Model

The constructs in Student's Attitudes Toward Statistics – Model (SATS-M) focus on the "multi-dimensional and longitudinal nature of students' attitudes and course outcomes" (Ramirez et al., 2012, p. 62). SATS-M enables researchers to understand why some students perform and value statistics more than other students and why they make different life and academic choices (Chiesi & Primi, 2010; Hood, Creed & Neumann, 2012; Sorage & Schau, 2002).

SATS-M was first conceptualized in the design of the Students' Attitudes Toward Statistics survey, SATS-28© (Schau et al., 1995), which measures the four attitude dimensions of: *Affect*, *Cognitive Competence*, *Value*, and *Difficulty* (italics in original article). The *Affect* component consists of six items regarding students' feelings concerning statistics. The *Cognitive Competence* component consists of six items regarding students' attitudes about their intellectual knowledge and skills when applied to doing statistics. The *Value* component consists of nine items regarding students' attitudes about the usefulness, relevance, and worth of statistics in their personal and professional lives. The *Difficulty* component consists of seven items regarding students' attitudes about the difficulty of statistics as a subject.

Three expectancy-value factors in Eccles and colleagues' model were the most used in the development of SATS-28©; these factors include: "(1) Expectancies for success – students' self-concepts regarding their ability to do statistics successfully; (2) Task Difficulty – students' perception of the difficulty of statistics; and (3) Task value – students' perceptions of the value of doing statistics successfully" (Schau, 2003b, p. 7).

Duphinee, Schau, and Stevens (1997) confirmed the four-factor structure of SATS-28©. They used a sample of 991 undergraduate students enrolled in introductory statistics courses in the psychology, sociology, management, mathematics and statistics programs at a large

Southwestern university in the U.S. The data was collected in the fall of 1991 and spring of 1992. The participants completed the pre-version of SATS-28© in the first week of classes.

Duphinee et al. (1997) used Confirmatory Factor Analysis for testing the invariance structure of SATS-28© for both male and female responses. The attitudes components of Affect and Cognitive Competence were strongly related (r = 0.94), which raised the issue of whether these two components overlap or should remain distinct. However, the goodness-of-fit measures suggested that the data fit the four-factor solution reasonably well. The correlation between the attitudes components of Value and Difficulty was not statistically significant. The correlations between attitudes components of Value and Affect, and Value and Cognitive Competence were moderately low. The variability in the Value attitudes scores was larger for the female participants than for males. Duphinee et al. (1997) suggested that female participants viewed the value (worth, relevance, and usefulness) of the subject of statistics to their professional and academic lives differently than the male participants. The relationship between Affect and Value attitudes components was stronger for the males (r = 0.48) than for the females (r = 0.33). The authors suggested that more male students liked statistics than female students, and that male students viewed the subject as more valuable to their professional and academic lives.

SATS-28© was later updated to SATS-36© (Schau, 2003a, 2003b), with the two additional attitudes components of *Interest*, and *Effort* (italics in original article). The *Interest* Component consists of four items regarding students' level of individual interest in statistics. The *Effort* component consists of four items regarding amount of time and effort students invest in learning statistics. Moreover, SATS-36© includes three additional items that assess students' global attitudes of *math cognitive competence, statistics cognitive competence*, and *career value* (italics in original article). There are two versions of SATS-36©, pre- and post-surveys. The pre-survey of SATS-36© is in Appendix A and post-survey of SATS-36© is in Appendix B.

Each of the six components and the additional items in SATS-36© are congruent with Eccles' et al. (1983) expectancy-value model. The *Affect* component is congruent with affective memories. The *Cognitive competence* component is congruent with self-concepts of one's abilities and expectation for success. The *Value* component is congruent with attainment value and utility value. The *Difficulty* component is congruent with perception of task demand. The *Interest* component is congruent with interest-enjoyment value. The *Effort* component is congruent with the cost component—how much effort and time is needed to complete a task. The *Math cognitive* component is congruent with previous related-achievement in mathematics. The *Statistics Outcomes* component is congruent with related-achievement choices and performance.

2.5.1 Reliability of SATS-36©

It is important to examine the quality of scores from any instrument to indicate that the scores are reliable and valid for their psychometric properties (Creswell, 2012). Scores on any instrument are reliable or accurate if an individual score is internally consistent across the instrument (Creswell, 2012). Furthermore, responses to a survey that is administered at different times should be relatively similar (Creswell, 2012). SATS-36© has typically been administered twice, once at the beginning and another time at the end of an introductory statistics course.

Numerous studies provided high internal consistency for the six attitudes components of SATS-36©. Based on recent studies (Carnell, 2008; Emmioglu, 2011; Tempelaar, Schim van der Loeff & Gijselaers 2007; Verhoeven, 2009), Cronbach's alpha coefficients (Cronbach, 1984) for the six attitudes components of SATS-36© were reported as the following: 0.80-0.82 for Affect, 0.77-0.85 for Cognitive Competence, 0.77-0.88 for Value, 0.68-0.79 for Difficulty, 0.80-0.90 for Interest, and 0.76-0.80 for Effort.

2.5.2 Validity of SATS-36©

For establishing the validity of any instrument, the components of that instrument need to match its hypothesized model (Creswell, 2012). Studies regarding students' attitudes toward statistics employed Confirmatory Factor Analysis (CFA) in the Structural Equation Modelling technique and confirmed the hypothesized model of attitudes toward statistics with SATS-36© (Emmioglu, 2011; Tempelaar et al., 2007) or with SATS-28© (Hilton, Schau & Olsen, 2004). Additionally, the four attitudes components of: Affect, Cognitive Competence, Value and Difficulty in SATS-28© were shown to be invariant by gender, by time of test administration, and both by gender and time of test administration (Hilton et al., 2004).

2.5.3 Conceptual Structure of Statistics Attitudes-Outcomes Model

Figure 2, on page 43, presents the conceptual structure of Statistics Attitudes-Outcomes Model (Emmioglu, 2011). Math Achievement includes perception of past mathematics achievement. Attitudes toward statistics includes the six attitudes components of: Affect, Cognitive Competence, Difficulty, Value, Interest, and Effort (Schau, 2003b). Statistics Outcomes includes statistics course grade, willingness to use statistics in the remainder of the degree program (e.g., in Sociology, Education), and willingness to use statistics when employed.

In the Statistics Attitudes-Outcomes Model (Figure 2), the component of Statistics Outcomes is defined by past mathematics achievement, Affect, Cognitive Competence, Value, and Effort components. The Affect component is defined by past mathematics achievement and Cognitive Competence components. The Cognitive Competence component is defined by past mathematics achievement and Difficulty components. The Value component is defined by Affect and Interest components. The Interest component is defined by Affect, Cognitive Competence, and Difficulty components. Lastly, the Effort component is defined by Cognitive Competence and Interest components.

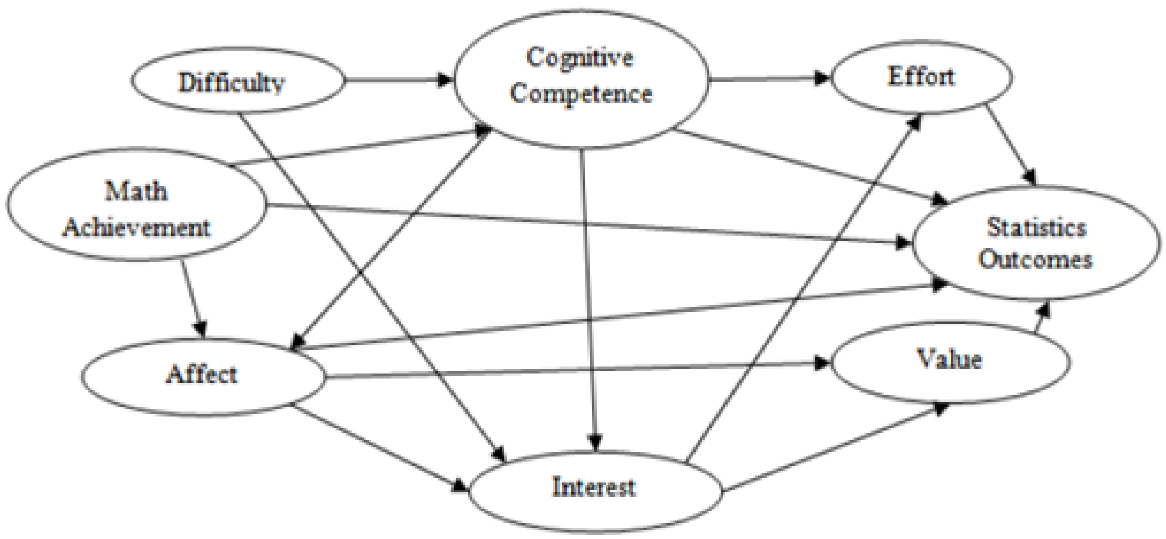

Figure 2. Conceptual Structure of the Statistics Attitudes-Outcomes Model (Emmioglu, 2011, p. 8)

2.6 Studies on Students' Attitudes Toward Statistics

In this section, I provide summaries of recent studies on students' attitudes toward statistics. Most of these studies used either SAT-28© or SAT-36© to examine the changes in students' attitudes towards statistics or to assess the interrelationships between students' attitudes toward statistics and their statistics outcomes.

Sorge and Schau (2002) report the result of their study conducted in the fall of 1999 and spring of 2000 at a major Southwestern university in the U.S. Their study examined the interrelationships among 264 undergraduate engineering students' previous academic success, their attitudes toward statistics, and their achievement in an introductory statistics course. To investigate these relationships, they created, tested, and modified the Statistics Attitudes-

Achievement Model based on Eccles et al.'s (1983) expected-value theory and its application to statistics education. The post-version of SATS-28© was administered to the participating students during the last eight-days of their statistics course. Sorage and Schau (2002) used the Structural Equation Modelling technique to fit the adequacy of their data to their hypothesized model.

The results of Sorage and Schau (2002) revealed that those students who did well in their previous academic courses (e.g. high school mathematics) and had positive feelings concerning statistics obtained high grades in their statistics course. Those students who perceived themselves as more intelligent and capable of doing statistics had higher positive feelings concerning statistics at the end of their introductory statistics course and, in turn, they had higher statistics achievement. Those who perceived statistics as a less difficult subject indicated higher capabilities to do statistics, which positively affected their view of statistics, and, in turn, they valued the subject more at the end of their introductory statistics course.

Based on their findings, Sorge and Schau (2002) suggest to instructors of introductory statistics courses that they assess students' attitudes about statistics at the beginning of their course so that they can identify those students who will have challenges with learning and appreciating statistics. In that case, teachers can provide appropriate support to their students and prevent them from failing or dropping the course.

Schau (2003b) discusses the findings of her study on assessing attitudes about statistics for a subsample of students in an introductory statistics course, which was offered by the Department of Mathematics and Statistics at a major Southwestern university in the U.S. The data collected on students' attitudes toward statistics contributed to the development and testing of SATS-28© (Schau et al., 1995; Dauphinee, Schau & Stevens, 1997). Students' responses to

SATS-28© were collected from 11 sections of the same introductory statistics course over the course of two consecutive semesters. 580 students completed the pre-version of the SATS-28© within the first two weeks of their introductory statistics course. 287 of these students completed the post-version of the SATS-28© within the last two weeks of their statistics course.

The findings from Schau's (2003b) study revealed that most students ascribed their attitudes about statistics to their previous achievement and teachers. The results of her descriptive statistical analysis for the pre- and post-tests data revealed that, on average, students' attitudes-scores about their competency in statistics and their valuing of the subject were the highest and positive. Students neither liked nor disliked the subject of statistics and perceived the subject as somewhat difficult at both times of the test administration. The mean attitudes-scores in all four attitudes components slightly dropped from the beginning to the end of the course. Male and female students had similar pre-course attitudes and valued the subject equally at the end of the course. Male students had slightly higher post-course attitudes than the female students regarding their feelings concerning statistics, their competency in statistics, and their perception of statistics as a less difficult subject.

Schau (2003b) found small to moderate positive relationships between students' attitudes and their statistics course achievement, with larger relationships for post-test scores. Students' competency in and affect toward statistics explained about 12% of the variance in the course grade, whereas their valuing of the subject explained about 9%. Based on her findings, Schau (2003b) suggests that instructors distinguish the subject of statistics from mathematics for their students, and emphasize that basic mathematical skills (e.g., basic algebra skills) are needed in a statistics course. She also suggests allowing students to bring cheat sheets to the tests and to the exam for the purpose of alleviating their stress. She adds that providing students with the opportunity to create cheat sheets is an effective study technique. She also encourages instructors to demonstrate positive attitudes themselves, to use humour in class and to be supportive and organized.

Mills (2004) used SATS-28© to assess students' attitudes towards statistics in the first weeks of their introductory statistics course. The participants were 203 undergraduate students enrolled in an introductory statistics course at a large Southeastern university in the U.S. Mills (2004) indicated that, overall, students had more positive than negative attitudes about statistics. The students reported that they like and can learn statistics, and can understand statistics equations. They also expressed that statistics should be part of their professional training and that they use statistics in their everyday life. Male participants were more likely than female participants to report that they can learn statistics, that they felt more confident mastering statistics materials, and were not scared by statistics. Based on his results, Mills (2004) suggests that more attention should be given to improving female students' attitudes toward statistics.

Similar to Utts (2003) and Rumsey (2002), Mills (2004) recommends that instructors use readily available statistical packages in an introductory statistics course when doing tedious calculations and constructing graphs. In doing so, instructors can emphasize to their students the ways in which statistics is applicable to real-world problems.

Hilton, Schau, and Olsen (2004) extended the work of Dauphinee, Schau, and Stevens (1997) on confirming the invariance structure of SATS-28© for male and female participants. Hilton et al. (2004) examined the variance structure of SATS-28© by gender, time of test administration, and both by gender and time of test administration for a large sample of 5360 undergraduate students enrolled in introductory statistics courses offered by statistics departments over the course of four semesters from 1998 to 2000 at Brigham Young University in the U.S. Like Dauphinee et al. (1997), they confirmed the invariance structure of SATS-28© by gender of participants. However, the result of their confirmatory factor analysis revealed larger variations in the post-semester responses to SATS-28© items. They reported that larger variations for post-SATS scores are expected after students' experience of their introductory statistics course.

Hilton et al. (2004) confirmed the invariance structure of SATS-28© by gender and time of test administration. They indicate that their findings can enable future researchers to work with mean components of SATS-28©. For example, researchers can compare the mean attitudes components across gender and time of test administration to investigate changes in students' attitudes toward statistics from the beginning to the end of an introductory statistics course. Hilton et al. (2004) add that researchers can examine the relationship between students' attitudes and their statistics achievement, while accounting for their previous related-achievements in mathematics or statistics courses.

Carmona, Martinez, and Sanchez (2005) examined the relationship between students' mathematical background and their initial attitudes about statistics. The participants were 827 undergraduate social sciences students who enrolled in introductory statistics courses at two Spanish universities. The participating students completed SATS-28© during the first two weeks of their course. Additionally, they provided information regarding the grades they obtained in their previous mathematics courses and the types of mathematics courses that they took at the high school level. The authors reported that, in Spain, students can take different high school mathematics courses depending on their focus of study (e.g., Arts, Social Sciences, Natural Sciences, and Technology). The level of complexity of these high school mathematics courses differ according to students' choice of study. The Arts students receive low levels of mathematics exposure; Social Sciences students receive a medium level, and Natural Sciences and Technology students receive high levels of mathematics exposure.

Carmona et al. (2005) conducted a multivariate analysis of variance to test the relationship between students' previous mathematics exposure and their attitudes toward statistics. The levels of mathematics exposure were treated as the between-subject factor. Moreover, they performed a multivariate analysis of covariance, treating students' grades in their previous mathematics course as their covariate in their model. Their results revealed that expectations for students' perceived level of difficulty of the subject of statistics, their feelings toward, their competency in, and their valuing of the subject were positive. Students who had low levels of previous mathematics exposure had the least positive attitudes, whereas those with high levels of previous mathematics exposure had the most positive attitudes. Students' previous grades in mathematics showed the strongest correlations with their affect toward, and competency in statistics. This correlation was stronger for those students who had high levels of high school mathematics exposure. Those students with low levels of high school mathematics exposure, and who obtained poor grades in those courses, valued the subject of statistics less.

Based on their findings, Carmona et al. (2005) conclude that previous successful achievements in mathematics can influence students' attitudes toward statistics. They add that, for the purpose of enhancing students' self-efficacy in statistics, students can benefit from taking a remedial mathematics course prior to or simultaneously with their statistics course.

Cashin and Elmore (2005) used SATS-28© to investigate the relationship among students' previous number of mathematics courses, their attitudes toward statistics at the beginning and at the end of their introductory statistics course, and their course performance. For their study, they recruited 342 undergraduate and graduate students enrolled in two introductory statistics courses at a large Midwestern university in the U.S. The results of their study revealed that all four attitudes components in SATS-28© had small positive correlations with the number of previous mathematics courses that students took. Those students who took a greater number of mathematics courses prior to their statistics course reported more positive attitudes at the beginning of their statistics course. Older students perceived the subject of statistics to be more difficult, and perceived themselves as less capable of doing statistics than the younger students.

Cashin and Elmore (2005) found that all four attitudes components were positively related to statistics course performance. Those students who exhibited more positive attitudes about statistics achieved more in their statistics course. The post-course attitudes had stronger positive relations with the statistics course performance. Students' affect toward statistics had the highest correlation with their course performance, whereas their perceived difficulty of the subject of statistics had the lowest. Students' pre- and post-course attitudes-scores explained about 21% of variance in their statistics course performance over and above their demographics of age, their gender, and their previous number of mathematics courses completed. Cashin and Elmore (2005) found no statistically significant differences between male and female students' course performance and their attitudes toward statistics. The authors conclude that students' attitudes toward statistics are important contributions for explaining their statistics course outcomes.

Tempelaar, Schim van der Loeff, and Gijselaers (2007) examined the interrelationships among students' prior attitudes toward statistics, their prior statistical reasoning, and their statistics course outcome. The participants were 1618 first-year undergraduate students in International Business and International Economics Programs enrolled in a quantitative methods course. The authors used SATS-36© to collect data on students' attitudes about statistics. The results of their study revealed that, overall, students expressed positive attitudes concerning their feelings toward statistics, their competence in doing statistics, their perception of valuing the subject of statistics, their interest in learning statistics, and their willingness to spend more time in doing statistics. However, they perceived the subject of statistics as somewhat difficult.

Tempelaar et al. (2007) found that those students who viewed the subject of statistics positively felt more capable of doing statistics, valued the subject more, perceived the subject as less difficult, and were more interested in statistics. Those students who perceived themselves as more intelligent and capable of doing statistics valued the subject of statistics more, perceived the subject as less difficult, were more interested in statistics, and reported spending more effort in learning statistics. For students who valued the subject of statistics more, their interest in and their reported amount of time spent learning statistics were higher. For those students who perceived the subject of statistics as less difficult, their reported amount of effort in learning statistics was low. Students who were more interested in statistics reported spending more time to learn statistics. Based on their findings, the authors indicated that students' competencies with statistics were a strong predictor for their statistics course performance.

Dempster and McCorry (2009) conducted a study that examined the relationships among undergraduate psychology students' previous experiences of mathematics, statistics and computing, their attitudes toward statistics, and their statistics assessment. SATS-28© was used to collect students' responses regarding their attitudes about statistics. 154 psychology students in the first semester of year 1 of their program of study completed the pre-course attitudes survey. 103 psychology students in the second semester of year 2 of their program of study, which was after completing all the four required statistics courses for their degree requirement, completed the post-course attitudes survey.

Dempster and McCorry (2009) matched the responses of 82 students from the post-course attitudes survey with their pre-course attitudes survey. The authors found no statistically significant mean differences between pre- and post-test scores in any of the four attitudes component. The result of their descriptive statistical analysis revealed that the participants' ratings of their mathematical ability and their previous experience of computing were positive. However, their previous experiences with statistics were somewhat negative. Those students who perceived their mathematical ability positively viewed the subject of statistics positively, felt more capable of doing statistics, and valued the subject of statistics more, obtained higher statistics course assessment.

Dempster and McCorry (2009) reported that, by the end of the second year of their study, students who felt more capable of doing statistics, obtained higher statistics course assessment. Additionally, students who viewed the subject of statistics positively perceived the subject as less difficult, and valued the subject more. The authors also conducted a mediation analysis, and the result of that analysis showed that students' belief about their statistical competencies held at the beginning of their course (e.g., in year one) will likely mediate the relationship between their perception of their mathematical abilities and their statistical competencies at the end of their statistics course (e.g., in year two).

Like Carmona et al. (2005), Dempster and McCorry (2009) suggest that departments offering introductory statistics courses design and deliver a remedial mathematics course to those students who need to enhance their mathematical foundations, which are necessary skills for understanding statistical concepts. They also suggest that instructors rely on their students' intuition for enhancing students' self-efficacy about statistics. For instance, they suggest that instead of relying on a mathematical formula, when asking students to estimate the mean value for a data set, instead provide them with small set of data values so that they can use their intuition for estimating the average.

Chiesi and Primi (2010) conducted a path analysis to examine the interrelationships among students' previous mathematical achievement, their mathematical competency at the beginning of an introductory statistics course, their statistical anxiety during the course, their attitudes toward statistics at the beginning and at the end of the course, and their statistics course achievement. The participants were 487 undergraduate psychology students. SATS-28© was used to assess students' pre- and post-course attitudes about statistics. Chiesi and Primi (2010) reported that students' mathematical background (high school performance in mathematics) had a positive significant association with their initial mathematical knowledge as assessed at the beginning of their course. Students' mathematical background had a positive indirect effect on their pre-course attitudes and a negative indirect effect on their statistical anxiety during the course through their initial mathematical knowledge. Students' initial mathematical knowledge had a strong positive association with their statistics achievement at the end of their course, and had a moderate positive association with their pre-course attitudes about statistics. However, the association between students' initial mathematical knowledge and their statistics anxiety during the course was weak and negative.

Chiesi and Primi (2010) indicated that students' initial mathematical knowledge had positive indirect effects on their post-course attitudes through statistical anxiety, and on their statistics achievement through their statistical anxiety and their post-course attitudes about statistics. Students' pre-course attitudes had small positive indirect effects on their statistics achievement through their post-course attitudes, and on their post-course attitudes through their statistical anxiety during the course. The authors found that, overall, students' attitudes towards statistics improved by the end of their course. Moreover, they found that students with high initial mathematical knowledge had positive feelings about statistics, and perceived the subject of statistics as less difficult by the end of their course.

Emmioglu (2011) examined the interrelationships among Turkish students' past mathematics achievement, their attitudes toward statistics, and their statistics outcomes (their statistic course grade and their willingness to use statistics in the remainder of their degree program and when employed). Emmioglu (2011) tested a structural model that she named "Statistics Attitudes-Outcome Model", which was presented earlier in this thesis (Figure 2). The participants were 247 undergraduate and graduate students enrolled in education, engineering, and economics programs. She administered the post-version of SATS-36© for testing the overall fit of her data to her proposed model. Her structural model explained 66% of variation in students' statistics outcomes. Students' feelings toward statistics, their valuing of the subject, their perception of their capability to do statistics, and their interest in statistics were larger contributors to explaining the variation in their statistics outcomes than their past mathematics achievement and their effort to learn statistics.

The results of Emmioglu's (2011) descriptive statistical analysis revealed that students had positive views regarding their past mathematics achievement and positive attitudes regarding their feelings towards statistics, their capability of doing statistics, their perception of statistics as a valuable subject, and their willingness to spend time in doing statistics. However, they perceived the subject of statistics as neither easy nor difficult, and had neutral views regarding their interest in statistics.

Emmioglu (2011) examined students' attitudes toward statistics according to their sex and by their year of study. She found no statistically significant differences of mean attitudes components between male and female students, and among students' different years of study. Statistics outcomes were high for those students who had positive views for past mathematics achievement, feelings about statistics, feelings of capability in doing statistics, valuing the subject more, interest in statistics more, and spending more time in doing statistics. Students' past mathematics achievement did not directly contribute to explaining their attitudes about statistics. However, those students who perceived themselves as doing well in their past mathematics courses and reported putting lots of effort into learning statistics obtained high statistics outcomes.

Emmioglu (2011) indicated that those students who felt capable of doing statistics, and had positive views concerning statistics, were more interested in statistics, and in turn had higher statistics outcomes. Those students who were more interested in statistics, valued the subject more, put more effort into learning statistics, in turn had higher statistics outcomes. Based on her findings, Emmioglu (2011) suggests that instructors assess their students' attitudes toward statistics and students' initial mathematical and statistical knowledge at the beginning of the course in order to design and deliver their statistics courses appropriately.

Schau and Emmioglu (2012) examined about 2200 post-secondary students' attitudes toward statistics across 101 sections of introductory statistics service courses in the U.S. between 2006 and 2010. About 93% of these sections had between 10 and 50 students enrolled in their introductory statistics courses, and only 2% of sections had more than 50 students in their classes. Their merged data contained students' responses to SATS-36© collected once at the beginning (pre-test) and another time at the end (post-test) of introductory statistics courses.

Schau and Emmioglu (2012) found no statistically significant correlations between the number of participants who took SATS-36© in different section sizes and their mean attitudes for different time of test administration. They also found no meaningful section mean differences in any of the attitudes components by institution type (four-year and advance degree-granting). The result of their descriptive statistical analysis revealed that, at the beginning of introductory statistics courses, regardless of assessing attitudes by sections (101 sections) or by total number of students' responses (about 2200), on average, students neither liked nor disliked statistics. They perceived statistics as a somewhat difficult subject. They somewhat valued the subject of statistics for their academic and professional lives. They believed that they would be capable of doing statistics. They were somewhat interested in learning statistics. They indicated that they would spend a significant amount of time to learn statistics.

Schau and Emmioglu (2012) indicated that, at the end of their introductory statistics courses, students still, on average, neither liked nor disliked statistics. They still perceived the subject of statistics as somewhat difficult. They believed that they were capable of doing statistics. They were less interested in learning statistics. They still valued the subject of statistics for their academic and professional lives. However, about 25% of the sections dropped their scores from positive views regarding the valuing of subject of statistics to neutral scores.

Schau and Emmioglu (2012) indicated that, at the end of their introductory statistics courses, students still reported spending a significant amount of time in learning statistics. However, their reports of anticipated effort needed to learn statistics at the end of the course were less than what they initially reported at the beginning of their course. Based on their findings, Schau and Emmioglu (2012) suggest that researchers and instructors consider the relationships between students' attitudes toward statistics and the structure of statistics courses, the lecture sections that students choose to enrol in, the ways in which students are evaluated in their statistics course, and students' characteristics.

Bond, Perkin and Ramirez (2012) investigated how students define and conceptualize statistics at the beginning and at the end of the course. Additionally, they investigated the relationship between students' definitions of and conceptualizations of statistics with their attitudes toward statistics. The authors used SATS-36© to assess students' attitudes toward statistics. 47 post-secondary students in the U.S. completed the pre-course attitudes survey and the pre-perceptions survey. From those students, 37 completed the post-perceptions survey and 38 of them completed the post-course attitudes survey. Most of their participating students (77%) had not taken a statistics course prior to their current course.

Bond et al. (2012) results revealed that, at the beginning of the course, most students defined statistics as based on the notion of descriptive statistics (mean, median, and mode), whereas, by the end of the course, most students defined statistics as based on ideas around inferential statistics. 66% of the students had inaccurate definitions of statistics at the beginning, whereas 97% of the students had accurate definitions of statistics by the end of the course.

In terms of students' attitudes toward statistics, Bond et al. (2012) results revealed that, at the beginning of the course, students had somewhat positive feelings about statistics, had high competency in doing statistics, valued the subject of statistics for their professional and academic lives, were interested in statistics, and expected to invest more time in learning statistics. However, they perceived the subject of statistics as somewhat difficult. With the exception of students' post-scores regarding their perception of statistics as a difficult subject, their affect toward, their competency in, their valuing of, their interest in, and their effort to learn statistics remained positive by the end of their introductory statistics course. However, students' scores in terms of their interest in statistics dropped, which indicated that they were less interested in statistics by the end of their statistics course.

Hood, Creed and Neumaan (2012) examined the structural relationships among students' attitudes towards statistics, their past performance in a statistics course, and their statistics achievement. The participants were 149 psychology students who had completed an introductory research-methods course and a statistics course. Post-version of SATS-28© were administered to the participants as well as three additional items that assessed students' expectancy of success. The results of their study showed that students somewhat perceived statistics as difficult and felt somewhat negatively toward the subject. However, they somewhat felt competent, and realized the value of statistics to their academic and career lives. Students who performed better in their previous statistics course showed positive feelings about statistics, had high competence in doing statistics, valued the subject more, reported spending more time in studying for their statistics course, and had high expectancies for success; in turn, their statistics achievement was high. However, their past performance in statistics did not contribute to their perception of the difficulty of the subject of statistics.

Hood et al. (2012) found that for students who had reported higher competence in statistics, their feelings about statistics were more positive and, in turn, their expectations for success in their current statistics course and their valuing of the subject were also higher. Based on their findings, Hood et al. (2012) assert that, in order to foster successful statistics achievement and positive attitudes about statistics, teachers need to use strategies that can simplify concepts for their students, while emphasizing the value of learning statistical concepts to their students' future professional goals. Moreover, they add that instructors should assess students' background knowledge in mathematics and statistics, and based on those initial assessments, support students who have poor foundational skills in these subjects so that they can succeed in their course.

Arumugam (2014) investigated the relationships among students' past mathematics achievement, their attitudes toward statistics, and their statistics outcomes. The participants were 244 undergraduate students enrolled in public universities in Kuala Terengganu. Arumugam (2014) tested the modified "Statistics Attitudes-Outcomes Model" (SATS-41) using Confirmatory Factor Analysis (CFA). The results of her CFA revealed that the data fitted the hypothesized model of SATS-41. Those students who had positive views about statistics felt capable of doing statistics, valued the subject more, and were more interested in statistics. Those students who perceived statistics as a less difficult subject, felt capable of doing statistics, and were interested in statistics. Those students who were interested in statistics valued the subject more, and put more effort into learning statistics. Those students who reported doing well in their previous mathematics courses, felt capable of doing statistics, believed in their ability to understand and carry out statistical tasks, and valued the subject of statistics, had high statistics outcomes.

Like previous researchers (e.g. Bond et al., 2012; Emmioglu, 2011; Hood et al., 2012), Arumugam (2014) suggests that instructors consider their students' prior foundational skills in mathematics and deliver their statistics course appropriately based on their students' past mathematics achievement. Like Emmioglu (2011), Arumugam (2014) advocates that instructors incorporate fun, engaging, and relevant activities into their statistics courses so that students become motivated to use statistics outside of their classroom.

2.6.1 Summaries of Studies on Students' Attitudes Toward Statistics

There are many studies that used the Survey of Attitudes Toward Statistics (SATS©), which investigated the relationships among students' attitudes about statistics, their statistics achievement, and their previous achievements or experiences in similar mathematics or statistics courses (e.g., Cashin & Elmore, 2005; Dempster & McCorry, 2009; Hood et al., 2012). It can be summarized that perceptions of mathematical capability and past achievements in mathematics or statistics are useful predictors of statistics achievement (Emmioglu, 2011; Hood et al., 2012; Sorge & Schau, 2002). Those students who reported doing well in their past mathematics or statistics courses had high statistics achievement. Moreover, those who reported doing well in their past mathematics or statistics courses had positive views concerning statistics, felt more capable in doing statistics, valued the subject of statistics more (e.g., Arumugam, 2014; Dempster & McCorry, 2009; Hood et al., 2012), and put a great deal of effort into learning statistics (Emmioglu, 2011; Hood et al., 2012). Those students who had positive views concerning statistics, felt competent in their capabilities of doing statistics, valued the subject to their academic and professional lives, perceived the subject as less difficult, were interested in statistics, and put a great deal of effort to learn statistics, had high statistics course outcomes (e.g., Arumugam, 2014; Dempster & McCorry, 2009; Emmioglu, 2011; Hood et al., 2012; Schau, 2003b).

Overall, students had neutral to positive feelings about statistics, felt capable in doing statistics, valued the subject to their academic and professional lives, were interested in statistics, and reported spending a great deal of effort to learn statistics (e.g., Bond et al., 2012; Chiesi & Primi, 2010; Emmioglu, 2011; Schau & Emmioglu, 2012). However, they perceived the subject of statistics as somewhat difficult (e.g., Bond et al., 2012; Emmioglu, 2011; Hood et al., 2012; Schau, 2003b; Schau & Emmioglu, 2012). Studies that assessed changes in students' attitudes toward statistics reported that students' attitudes-scores toward statistics dropped from the beginning to the end of their statistics course (Bond et al., 2012; Schau, 2003b).

Those students who reported liking statistics felt capable of doing statistics, valued the subject more to their academic and professional lives, perceived the subject as less difficult, were more interested in statistics, and put more effort into learning statistics (e.g., Arumugam, 2014; Dempster & McCorry, 2009; Emmioglu, 2011; Tempelaar et al., 2007). Those students who felt capable of doing statistics also valued the subject more, perceived the subject as less difficult, were interested in statistics, and put more effort in learning statistics (e.g., Arumugam, 2014; Dempster & McCorry, 2009; Emmioglu, 2011).

Students who were more interested in statistics valued the subject more, and put more effort into learning statistics (Arumugam, 2014; Emmioglu, 2012; Tempelaar et al., 2007). Those students who perceived the subject as less difficult reported that they put less effort into learning statistics (Emmioglu, 2011; Tempelaar et al., 2007). Lastly, those students who were interested in statistics reported putting lots of effort into learning statistics (Arumugam, 2014; Emmioglu, 2011; Tempelaar et al., 2007).

For the current study, I adopted SATS-36©, which is based on Eccles et al.'s (1983) expectancy-value model of behaviour in mathematics achievement, to measure undergraduate social sciences students' attitudes toward statistics once at the beginning and again at the end of their introductory statistics course. From students' responses to the pre- and post-course surveys (SATS-36©), I examined how their attitudes toward statistics changed by the end of their course. I also investigated the relationships between students' attitudes toward statistics and their past mathematics achievements, their sex, their year of study, and their statistics course grade. Additionally, I examined the interrelationships among social sciences students' past mathematics achievement, their attitudes toward statistics by the end of their course, and their statistics outcomes (their statistics course grade, and their willingness to use statistics in the future).

Chapter Three: Methodology

3.1 Introduction

In this chapter, I describe the methodology for my study. I begin this section by providing an overview of the course under study: Introduction to Statistics for Social Sciences. After that, I explain the research design and my rationale for conducting a quantitative methodology. I then describe the participants, and present details of my study's procedure and data collection, and data analysis. I conclude this chapter by providing information regarding my study's ethical considerations.

3.2 Overview of the Course: Introduction to Statistics for Social Sciences

The Introduction to Statistics for Social Sciences course aims to develop students' statistical literacy. This means that students will learn basic statistical skills for reading and interpreting summary statistics and graphical displays in the social sciences. The course uses real data sets from the American and the Canadian General Social Survey (GSS), and the Organization for Economic Co-operation and Development (OECD) to explain statistical ideas to and motivate social sciences students. A web-based Survey Documentation Analysis (SDA) and a free statistical package, PSPP, are used for exploring these data sets. Students learn how to read and interpret summary statistics and graphical displays from both SDA and PSPP computer outputs. The course assessment includes ten weekly quizzes, a midterm test, a Read and Reflect group project, and a final exam. The instructions for the Read and Reflect course project is in Appendix C.

In the Read and Reflect project, students are required to work in groups of three to four members from similar programs of study. Each group is required to select a published paper form Statistics Canada, or a research paper from the social sciences that includes a quantitative methods section. Students are provided with instructions on how to reflect on their selected paper's statistical presentations (Appendix C).

Gal (2002) lists ten worrying questions that adults should consider when they encounter statistical messages. Inspired by Gal's view, I created seven components for consideration in how to read and reflect on a research paper that includes statistical messages (Appendix C). These components require students, as a group, to reflect on their selected paper's data collection, representations and interpretations of statistical messages. Component seven requires students to expand the scope of their selected paper by proposing a future research question and a statistical methodology that will answer that question. Component seven is concerned with developing students' habits of mind to think statistically (Chance, 2002).

Students are also provided with the Read and Reflect Success Criteria (Appendix D). The Read and Reflect success criteria outlines the due date, suggested timelines to work on specific components, the format of reflection submission, and the format of project assessment. Each group is required to submit their reflections on their chosen article's statistical information in a paper format.

In addition to the instructor's assessment of each group's reflections, each member of a group is expected to assess themselves and their peers based on four criteria. These criteria include: the extent to which a group member was accountable, productive, supportive, and creative (Appendix D). These criteria are explicitly defined so that students realize the importance of embracing their own and each other's responsibility for successful outcomes. Additionally, with these criteria, students are more likely to be motivated and motivate each other to collaborate, and put the effort needed in to completing their group project. Furthermore, these small groups can offer peer support during times such as preparation for the midterm test and the final exam.

3.3 Research Design

Based on the research questions of my study, I employed quantitative methodologies to examine students' attitudes toward statistics, and to investigate the relationships between their attitudes about statistics and their past mathematics achievement, their statistics course grade, their sex, and their year of study. Moreover, I used a quantitative methodology to examine the interrelationships among students' past mathematics achievement, their statistics attitudes at the end of their course, and their statistics outcomes (their statistics course grade, and their willingness to use statistics in the future).

The quantitative methodology reflects the philosophical underpinning of positivism, which asserts that knowledge (e.g., attitudes toward statistics) can be examined through observation and numeric data collection from a large number of people, which can help explain why individuals (e.g., social sciences students) behave the way they do (Sears & Cairs, 2010). For instance, a survey design can provide quantitative descriptions regarding a large number of individuals' attitudes (Creswell, 2012).

Furthermore, quantitative correlational design allows researchers to examine the relationships of responses to the questions in a survey with other variables in the data (Creswell, 2012). For my study, I employed a correlational technique and administered the Survey of Attitudes Toward Statistics (SATS-36©) twice in the course under study (once at the beginning and another time at the end of the course) to assess undergraduate social sciences students' attitudes toward statistics.

3.4 Participants

The participants for my study were undergraduate social sciences students who enrolled in the Introduction to Statistics for the Social Sciences course at a large urban university in the summer of 2016. There were 71 students enrolled in this course and 51 students (72%) agreed to participate in this study and completed both pre- and post-course survey (SATS-36©). The course under this study had three tutorial sections. There were 27 students registered in tutorial section 1; 18 students were registered in tutorial section 2; and, 25 students were registered in tutorial section 3.

Of the 27 students who were registered in tutorial section 1, 22 students (82%) agreed to participate in this study and completed both pre- and post-course survey (SATS-36©); 2 students (7%) were absent at both times of the survey administration; 2 students (7%) were absent at the time of pre-course survey administration; and, 1 student (4%) was absent at the time of post-course survey administration.

Of the 18 students who were registered in tutorial section 2, 11 students (61%) agreed to participate in this study and completed both pre- and post-course survey (SATS-36©); 1 student (6%) was absent at both times of the survey administration; 2 students (11%) were absent at the time of pre-course survey administration; 2 students (11%) were absent at the time of post-course survey administration; and, 2 students (11%) did not complete the pre- and post-course survey.

Of the 25 students who were registered in tutorial section 3, 18 students (72%) agreed to participate in this study and completed both pre- and post-course survey (SATS-36©); 2 students (8%) were absent at both times of the survey administration; 1 student (4%) was absent at the time of pre-course survey administration; and, 4 students (16%) were absent at the time of post-course survey administration.

3.5 Procedure and Data Collection

I was the instructor for the course. Therefore, a research assistant who had no connection to teaching and evaluation of students in the course collected data. During the first week of the tutorials, the research assistant visited the three tutorial sections and explained the study's goal to the students. After explaining the study's purpose to the students, the research assistant provided students with the consent form (Appendix E). Students who agreed to participate in the study were given the pre-course survey (SATS-36©) and were asked to complete the pre-course survey during the research assistant's visit.

During the last week of the tutorials, the research assistant visited the tutorials the second time and administered the post-course survey (SATS-36©) to those students who had agreed to participate and completed the pre-course survey (SATS-36©). Students were asked to complete the post-course survey during the research assistant's visit to their tutorials. The completion of each pre- and post-course survey (SATS-36©) took about 10 to 15 minutes.

For the 51 students who agreed to participate and completed both pre- and post-course surveys (SATS-36©), their final course grade was included in the data analysis. Furthermore, students were asked to provide their consent regarding the collection of additional information from the university's Registrar Office. This information included students' year of study, and their grades for their senior level mathematics courses at the high school level (e.g., the grades for their Mathematics of Data Management course in Ontario).

The research assistant assigned each participant a number code. In that case, I did not know which student participated or completed SATS-36© surveys. The data regarding students' final course grades, and the information that was obtained from the Office of the Registrar were forwarded to the research assistant. The research assistant linked student's responses to the pre-and post-course surveys (SATS-36©) with their course grade and the information that was received from the Office of the Registrar. Students' identifications (e.g., their first and last name, and their student number) were removed from the data before conducting statistical analyses. Thus, I worked with a de-identifiable data file for conducting data analysis.

3.6 Data Analysis

The participating students responded to each of the SATS-36© items using a 7-point Likert scale. The responses ranged from 1 (Strongly Disagree) through 4 (Neither Disagree nor Agree) to 7 (Strongly Agree). Within each SATS-36© component, the responses to the items were summed and divided by the number of items in that component (Schau, 2003b). Responses to items that were negatively worded were reversed before combining students' responses into component scores. Thus, higher mean responses reflect more positive attitudes.

To investigate the changes in students' attitudes, I used linear modelling procedure using Ordinary Least Squares (Kutner, Nachtsheim, Neter, & Li, 2005). Unlike t-tests, linear models can model dependence and will result in accurate estimates. Millar and Schau (2010) used linear modelling procedure in their study of assessing students' attitudes. They considered mean gained scores (pre-scores subtracted from post-scores), conditional on the pre-scores, rather than the overall mean gain. Thus, pre-scores were treated as predictor variables for their corresponding gain-scores. In the current study, to investigate the changes in students' attitudes, I followed the same statistical technique described by Millar and Schau (2010).

To examine the relationship between the sex of the respondents and their attitudes toward statistics at both times of the test administration, I employed mixed-design Analysis of Variance (ANOVA). I treated the sex of the respondents as the between-subject factor, and the time of test administration as the within-subject factor.

Also, to examine the relationship between the year of study of the respondents and their attitudes toward statistics at both times of the test administrations, I employed mixed-design ANOVA. I treated the participants' year of study as the between-subject factor, and the time of test administration as the within-subject factor.

To investigate the relationships between students' attitudes toward statistics at both times of the test administration and their past mathematics achievement, and their statistics course grade, I conducted Pearson correlations.

To examine the interrelationships among students' past mathematics achievement, their statistics attitudes by the end of their course, and their statistics outcomes (their willingness to use statistics in the future) I, like Emmioglu (2011), applied path analysis, a technique in structural equation modelling. Path analysis is like multiple regression that allows the researcher to examine the direct and indirect effects of variables on the dependent variables (Kline, 2011; Meyers, Gamst & Guarino, 2013). The estimated path coefficients are like those beta estimates in a multiple regression model (Meyers et al., 2013). With this technique, I examined my data's adequacy of fit to the hypothesized structural model (Emmioglu, 2011).

Since Emmioglu (2011) confirmed the structural relationships of her proposed model, in my path analysis, I treated the attitudes components as observed variables. Like Emmioglu (2011), I used students' responses to the post-course survey (SATS-36©) for testing the structural model. Additionally, I treated the attitude components of Affect, Cognitive Competence, Value, Interest, and Effort as endogenous variables, and Difficulty and Mathematics Achievement as exogenous variables. Endogenous variables are those where their assumed effects are explicitly presented in the model, whereas exogenous variables are those that are not predicted by other variables in the model (Kline, 2011).

Also, like Emmioglu (2011), I hypothesized the component of Statistics Outcomes as the main dependent variable, because it was expected to be predicted from other variables in the model. I investigated the magnitude of the direct and indirect effects of all other variables in the structural model on the main dependent variable, Statistics Outcomes.

For conducting the above-mentioned data analyses, I used a free statistical software R (version 3.3.1) to employ all the statistical analyses, including correlational techniques. Although the correlational method enables the findings from this study to be generalized to similar populations of students in introductory statistics service courses, casual relationships cannot be established (Agresti & Finlay, 2009). There might be some other unseen variables not included in the current study that might contribute to understanding social sciences students' attitudes toward statistics.

3.7 Ethical Considerations

My study was reviewed and approved by the Office of the Vice-President, Research and Innovation, and Human Research Ethics Programs at the University of Toronto. Undergraduate students in the social sciences programs at a large urban university who enrolled in the Introduction to Statistics for the Social Sciences course in the summer of 2016 were invited to participate in my study. Students were informed that their participation in the study was voluntary. Additionally, they were informed in the consent letter that they were free to withdraw from the study at any time. There was no penalty for withdrawing from this study. If students wished to withdraw form the study at any time, they were informed that their data, their responses to the attitudes survey items (SATS-36©), their information regarding their course grade and additional information received from the Office of the Registrar would be forever removed from the study's data set, and thus would not be included into the data analysis.

Chapter Four: Results

4.1 Introduction

In this chapter, I first describe how the data was screened for missing values and how the imputation method was used to input values for missing data. I then describe the influence of extreme data values (influential outliers) on the main statistical analyses. After that, I explain the results of checking the assumptions of multivariate and univariate normality, linearity, and homoscedasticity, which are necessary assumptions for conducting the main statistical analyses.

Next, I describe the results of demographic information regarding the participants' sex, their age, and their year of study in their degree program. Additionally, I report the year in which and the location where the participants obtained their high school diploma. Based on the obtained information from the participating university's Office of the Registrar, I describe students' past mathematics achievements and the types of mathematics courses they took at the high school level.

Based on students' past mathematics achievement, I describe the ways in which the participating students regarded their past performance in mathematics. I then describe participants' statistics course achievement and their statistics outcomes, which is a composite mean score of their statistics course grade and their self-ratings of their willingness to use statistics in the remainder of their degree programs and in their future employment.

Based on the participants' responses to the pre- and post-course surveys (SATS-36©), I describe students' attitudes toward statistics at the beginning and at the end of their introductory statistics course, as well as changes in their attitudes. I also describe students' attitudes toward statistics by their sex and their year of study. After that, I provide the results of the correlation analyses among the variables included in this study. These variables were students' self-ratings of their past performance in mathematics, their attitudes toward statistics at the beginning and at the end of the introductory statistics course under study, their statistics course achievement, and their statistics outcomes. Lastly, I demonstrate the results of the two main statistical analyses, the regression analysis and path analysis, for answering my research questions.

4.2. Data Screening

Before conducting any statistical analysis, the data needs to be screened for missing values and to ensure it meets the assumptions of normality, linearity, homoscedasticity and independence of errors (Meyers et al., 2013). The responses to negatively worded items on SATS-36© were reversed for conducting statistical analyses. Next, the data was examined for its patterns of missing values, influential outliers, assumptions of multivariate and univariate normality, and assumptions of linearity and homoscedasticity. A free statistical software R (version 3.3.1) was used to test these assumptions.

4.2.1. Missing Data

In this study, some of the items on SATS-36© had less than 3.92% of responses missing. The classical method of substituting missing values with their group mean (e.g., females) was used as an imputation method to deal with the missing data values (Meyers et al., 2013).

4.2.2 Influential Outliers

Outliers are extreme or unusual observations in a single variable (univariate) or combination of variables (multivariate) that can affect the result of a statistical analysis (Meyers et al., 2013). Since the current study includes multiple variables for subsequent statistical analyses, Mahalanobis distance statistics D^2 is used to detect the presence of multivariate outliers (Meyers et al., 2013). Mahalanobis distance statistics D^2 measures the multivariate distance between each observation and the group multivariate mean (Meyers et al., 2013). Mahalanobis D^2 for each observation is evaluated using the chi-square distribution with alpha-level of 0.001 (Meyers et al., 2013). Observations that reach the significance threshold (alpha-level of 0.001) are considered multivariate outliers (Meyers et al., 2013). Moreover, for the case of univariate outliers, z-scores are evaluated. A z-score measures how many standard deviations an observation is away from its mean (Agresti & Finlay, 2009). A z-score of beyond ± 3 value means its corresponding data value can be considered an outlier (Agresti & Finlay, 2009).

In the current study's pre-test data set, ten cases were detected as multivariate outliers, as they exceeded the critical value, $\chi^2(7) = 24.322$, $p < 0.001$. Boxplots of z-scores of pre-test data were examined to search for univariate outliers. The boxplots of pre-attitudes scores revealed three potential outliers in the Cognitive Competence component; two potential outliers in the Difficulty component; two potential outliers in the Value component, and one potential outlier in the Effort component. Examination of z-scores of the univariate outliers in the pre-test data revealed that only the Effort component (students' reports of their willingness to spend time to learn statistics at the beginning of their statistics course) had a z-score of -5.33, which was beyond -3. All the remaining potential outliers displayed in the boxplots of z-scores of pre-test data did not go beyond ± 3. Therefore, they were retained in the subsequent statistical analyses.

The influence of the extremely low z-score of -5.33 in the Effort component was further examined. As noted in the methods section (Chapter 3), the method of linear modelling procedure using Ordinary Least Squares (Kutner et al., 2005) is used to examine the changes in students' attitudes toward statistics. For example, gain-scores in the Effort component, which are the differences between pre- and post-scores in that component, were treated as the response variable conditional on its pre-scores. The scatterplot of gain-scores versus pre-scores in the

Effort component showed that, although the extremely low pre-score in the Effort component that had z-score of -5.33 was plotted farther from the overall data, it was plotted in the same direction as the remaining data points. Therefore, this data point was not considered as an influential outlier and was retained in the data set for the subsequent statistical analyses.

In the post-test data set, six cases were detected as multivariate outliers as they exceeded the critical value, $\chi^2(8) = 26.124$, $p < 0.001$. Boxplots of z-scores of post-test data were examined to search for univariate outliers. The boxplots of post-scores revealed three potential outliers in the Cognitive Competence component. Examinations of z-scores in the post-scores of the Cognitive Competence component revealed no values beyond ± 3. Therefore, these values were retained in the subsequent statistical analyses.

For the distributions of gain-scores, which were measured as changes in students' attitudes toward statistics from pre-test (at the beginning of the course) to post-test (at the end of the course), five cases were detected as multivariate outliers as they exceeded the critical value, $\chi^2(6) = 22.46$, $p < 0.001$. Boxplots of z-scores of gain-scores were examined to search for univariate outliers. The boxplots of gain-scores revealed several potential outliers. In the Affect component, there was one potential outlier with the z-score of 3.30, which was slightly beyond +3. In the Cognitive Competence, there were two potential outliers. However, their z-scores were not beyond ± 3 (one had z-score of -2.44, and the other one had z-score of 2.87).

In the Difficulty component, there was one potential outlier with z-score of -3.18, which was close to -3. In the Value component, there was one potential outlier with z-score of -2.74, which was not beyond -3. In the Interest component, there were two potential outliers, but with z-scores of about 2.56, which were not beyond +3. In the Effort component, there was one potential outlier with a z-score of -5.08, which was beyond -3. Based on the examination of the scatterplots of gain-scores versus pre-scores, the data values with extremely low or high z-scores were plotted in the same direction as the remaining data points. Thus, these extreme observations were not considered influential outliers and were retained in the subsequent statistical analyses.

4.2.3. Multivariate and Univariate Normality

Mardia's test was used to examine multivariate normality, which provides estimations of multivariate skewness ($\gamma_{1,p}^2$) and multivariate kurtosis ($\gamma_{2,p}^2$). If Mardia's estimations of multivariate skewness and kurtosis are statistically significant, at a significance level of 0.05, Chi-Square Quantile by Quantile (Q-Q) plot will be used to further assess the multivariate normality of the data (Korkmaz, Goksuluk & Zararsiz, 2014). Chi-Square Q-Q plot compares the probability distributions of observed quantiles (Squared Mahalanobis Distance) with the hypothesized quantiles (Chi-Square Quantiles). If the data is multivariate normal, the observed data fits the hypothesized distribution; the points in the Q-Q plot will approximately lie on the line $y = x$ revealing a 45-degree angle (Korkmaz et al., 2014).

However, if the Q-Q plot shows that the points deviate from the straight-line, there is an indication that the data departs from multivariate normality. In this case, Shapiro-Wilk's tests and univariate plots are useful to further diagnose the deviation from multivariate normality (Korkmaz et al., 2014). Stringent alpha-level (α = 0.001) is used against the result of Shapiro-Wilk's test to indicate a possible univariate normality violation (Meyers et al., 2013). If univariate normality is violated by either evaluation of Q-Q plot or Shapiro-Wilk's test, pairwise scatterplots should be assessed for their elliptical shapes, which, in this case, would be an indication that the departure from normality is acceptable (Meyers et al., 2013).

For the distributions of pre-scores, both Mardia's estimation of multivariate skewness ($\gamma_{1,p}^2$ = 21.73, p < 0.0001) and kurtosis ($\gamma_{2,p}^2$= 75.45, p < 0.0001) were statistically significant.

Both of these tests indicated that the pre-test data was not multivariate normal. Thus, Chi-Square Q-Q plot was produced to further assess the normality of the data. Chi-Square Q-Q plot showed that one data point deviated from the straight-line, which affected the multivariate normality of the data. Therefore, univariate normality of each distribution was assessed using Shapiro-Wilks's tests and univariate Q-Q plots.

The results of Shapiro-Wilk's tests revealed that all variables in the pre-test data except for the Effort component had univariate normal distributions at α = 0.001. The univariate Q-Q plots also suggested that the pre-scores in the Effort component departed from normality. The distribution of pre-scores in the Effort component was skewed to the left, because one data point was deviated from the straight-line. Based on the former examination of this value, its z-score was -5.33, which was beyond -3. However, the scatterplot of gain-scores versus pre-scores showed that this value with an extremely low z-score was plotted in the same direction as the rest of the data points. Therefore, it was not considered an influential outlier and was retained in the data.

For the distributions of post-scores, both Mardia's estimation of multivariate skewness ($\gamma^2_{1,p}$ = 16.56, p = 0.0944) and kurtosis ($\gamma^2_{2,p}$= 81.51, p = 0.6702) were not statistically significant. Both of these tests indicated that the post-test data was multivariate normal. Moreover, Chi-Square Q-Q plot showed that departure from multivariate normality was acceptable. In addition to the test of multivariate normality, univariate normality of each distribution was assessed using Shapiro-Wilks's tests and univariate Q-Q plots. The results of Shapiro-Wilk's tests revealed that all the variables in the post-test data had univariate normal distributions at α = 0.001. The univariate Q-Q plots also confirmed that all the variables in the post-test data had univariate normality.

For the distributions of gain-scores, which were measured as the changes in students' attitudes toward statistics from pre-test to post-test, both Mardia's estimation of multivariate skewness ($\gamma^2_{1,p}$ = 16.81, p < 0.0001) and kurtosis ($\gamma^2_{2,p}$= 63.48, p < 0.0001) were statistically significant. Both of these tests indicated that the distributions of the gain-scores were not multivariate normal. Therefore, Chi-Square Q-Q plot was produced to further assess the normality of the data. Chi-Square Q-Q plot showed that two data points deviated from the straight-line, which affected the multivariate normality of the data. Therefore, univariate normality of each distribution was assessed using Shapiro-Wilks's tests and univariate Q-Q plots.

The results of Shapiro-Wilk's tests revealed that all variables except for gain-scores in the Effort component had univariate normal distributions at α = 0.001. The univariate Q-Q plots also suggested that the gain-scores in the Effort component departed from normality. The distribution of gain-scores in the Effort component was skewed to the left, because one data point was deviated from the straight-line. Based on the former examination of this extreme value, its z-score was -5.08, which was beyond -3. However, as noted previously, the scatterplot of gain-scores versus pre-scores showed that this value with extremely low z-score was plotted in the same direction as the rest of the data points. Therefore, it was not considered an influential outlier and was retained in the data.

4.2.4 Linearity

Linearity refers to a linear relationship between two variables, and it can be assessed by checking bivariate scatterplots (Meyers et al., 2013). When a bivariate scatterplot shows an elliptical or oval shape, it indicates that a best-fitted function representing the scatterplot is a straight line, thus, the assumption of linearity is met (Meyers et al., 2013). In the current study, the inspection of scatterplots of gain-scores versus pre-scores for each of the six attitude components showed oval shapes. Therefore, these variables that were included in the subsequent statistical analyses were linearly associated with each other.

4.2.5. Homoscedasticity

The assumption of homoscedasticity means that quantitative response variables have equal levels of variability across the range of either continuous or categorical explanatory variables (Meyers et al., 2013). Levene's tests can be used to assess the homogeneity of variance assumptions (Meyers et al., 2013). If a Levene's test results in $p < 0.05$, then the assumption of homogeneity of variances is violated.

In the current study, the equal levels of variability across sex and the year of study of the participants were assessed for the quantitative variables included in the analyses. These variables include students' perception about past mathematics achievement, their grades obtained in their past mathematics course at the high school level, their responses to the six attitudes components of SATS-36© at the beginning and at the end of their statistics course, their statistics course achievement, and their statistics outcomes. All p-values of Levene's tests were not statistically significant at $\alpha = 0.05$. Thus, the assumption of homoscedasticity was met.

4.3 Demographic and Background Information of the Participants

There were 51 students who agreed to participate in this study, and completed both the pre- and post-course surveys (SATS-36©). Of all the participating students (n = 51), 32 students (63%) identified themselves as female and 19 students (37%) identified themselves as male. Most of the students (n = 39, 77%) had an age range of between 18 and 22 years. 12 students (23%) were older than 23.

Most of the students (n = 44, 86%) completed their high school in the province of Ontario; 3 students (6%) completed high school outside Ontario but elsewhere in Canada (one student in Alberta and two students in British Colombia); and, the remaining 4 students (8%) completed high school outside Canada (one student in South Africa, one student in Africa, one student in the U.S., and one student in Switzerland).

The majority (n = 38, 74%) of the students completed high school between 2009 and 2014; 4 students (8%) completed high school before 2009; and, 9 students (20%) completed high school in 2015. Of all the participants, 5 students (10%) were in the first year of their program of study; 11 students (22%) were in their second year; 14 students (27%) were in their third year, and, almost half of them (n = 21, 41%) were in the fourth year of their program of study.

4.4 High School Mathematics Achievement

Information regarding students' last high school mathematics achievement was obtained from the participating university's Office of the Registrar. At this participating university, students who intend to enrol into humanities or social sciences programs are not required to complete a grade 12 mathematics course. Of all the participants (n = 51), 21 students (41%) completed a grade 12 mathematics course (e.g., Advanced Functions, Calculus and Vectors, or Mathematics of Data Managements), whereas a majority (n = 30, 59%) did not. Of those students (n = 21) who completed a grade 12 mathematics course, a majority (n = 18, 86%) completed Advanced Functions (M = 77.22, SD = 8.75). Of those students (n = 21) who completed the Advanced Functions course, a majority (n = 11, 61%) completed Calculus and Vectors course (M = 74.09, SD = 9.16). Of all the participants (n = 51), 5 students (10%) completed Mathematics of Data Management course (M = 73.60, SD = 18.28).

Most of the participating students (n = 42, 82%) took a grade 11 mathematics course (e.g., Functions, Functions and Application, Mathematics of Personal Finance, Mathematics for Technology, or Mathematics for Everyday Life), whereas 9 students (18%) did not. Of those participants (n = 42) who took a grade 11 mathematics course, a majority (n = 26, 62%) took Functions (M = 67.31, SD = 16.64), which is a preparatory mathematics course for university; 9 students (21%) took Functions and Application (M = 64.89, SD = 12.83), which is a preparatory mathematics course for either college or university; 4 students (10%) took Mathematics of Personal Finance (M = 57.50, SD = 3.54); 2 students (5%) took Mathematics for Technology, and 1 student (2%) took Mathematics for Everyday Life and obtained a course grade of 54.

4.5 Past Mathematics Achievement

Participants were asked to rate how well they did in their past mathematics courses from 1 (very poorly) to 7 (very well). Past mathematics achievement (n = 51) had mean 3.32 and standard deviation of 1.49. This result indicates that, on average, students reported doing somewhat poorly in their past mathematics courses. This variable, past mathematics achievement is included in the main statistical analysis to investigate its relationship with students' attitudes toward statistics, and with their statistics outcomes at the end of the course.

4.5.1 Past Mathematics Achievement by Sex of the Respondents

Past mathematics achievement was examined according to the sex of the respondents. The female students had slightly lower mean past mathematics achievement (n = 32, M = 3.16, SD = 1.61) than the male students (n = 19, M = 3.37, SD = 1.30). However, the result of the independent t-test showed no statistically significant mean difference between male and female participants' past mathematics achievement ($t(49) = 0.49$, $p > 0.05$). The result of the t-test suggests that the mean difference between male and female participants' past mathematics achievement was negligible.

4.5.2 Past Mathematics Achievement by Year of Study of the Respondents

Past mathematics achievement was examined by the participants' year of study. Table 4.1 summarizes the means and standard deviations for past mathematics achievement by the year of study of the participants. The first-year (n = 5) students had the highest past mathematics achievement (M = 4.20, SD = 1.48). Their self-rating was slightly above the mid-point value of 4 on a Likert scale of 1 to 7, which indicates that they reported doing somewhat well in their past mathematics courses. The participating students in their second (n = 11) and third (n = 14) years of study had similar ratings (Table 4.1). Their self-ratings were, however, below the mid-point value of 4, which indicates that they reported doing somewhat poorly in their past mathematics courses. The participants in their fourth-year (n = 21) had the lowest past mathematics achievement (M = 2.86, SD = 1.59), which indicates that they reported doing poorly in their past mathematics courses.

Table 4.1

Means and Standard Deviations for Past Mathematics Achievement by Year of Study of the Respondents

Participants' Year of Study	*n*	*M*	*SD*
1	5	4.20	1.48
2	11	3.55	1.21
3	14	3.21	1.48
4	21	2.86	1.59

Analysis of Variance (ANOVA) was conducted to investigate whether there was any statistically significant mean difference of past mathematics achievement for participants' different years of study. In addition to the significance test, the strength of the effect size was calculated. The result of the ANOVA revealed that there were no statistically significant mean differences of past mathematics achievement for different years of study of the participants ($F(3, 47) = 1.33$, $p > 0.05$). Moreover, when the strength of the association was investigated, the value of the effect size was small, $\eta^2 = 0.08$, which means that students' year of study accounted for 8% of the variation in their past mathematics achievement.

4.6 Statistics Achievement

Statistics achievement is measured as the final course grade in the course under study. This variable takes the summation of grades for a quiz average that accounts for 20% of the final course grade, a course project that accounts for 10% of the final course grade, a midterm test that accounts for 30% of the final course grade, and a final exam that accounts for 40% of the final course grade. For all the participating students (n = 51), statistics achievement had mean 70.39 and standard deviation of 13.50.

4.6.1 Statistics Achievement by Sex of the Respondents

Statistics achievement was examined by the sex of the participating students. The female students had slightly lower statistics achievement (n = 32, M = 70.63, SD = 13.26) than the male students (n = 19, M = 71.74, SD = 9.80). However, the independent t-test showed no statistically significant mean difference between male and female participants' statistics course achievement ($t(49) = 0.32$, $p > 0.05$). The result of t-test suggests that the mean difference between male and female participants' statistics achievement was negligible.

4.6.2 Statistics Achievement by Year of Study of the Respondents

Statistics achievement was examined by the year of study of the participating students. Table 4.2 summarizes the means and standard deviations for statistics achievement by the year of study of the participants. Students in their first year of studies (n = 5) had the highest statistics achievement (M = 80.80, SD = 7.85). Statistics achievements for the second, third, and fourth-year participants were somewhat the same (Table 4.2). The second-year students had the lowest statistics achievement (M = 67.91, SD = 12.14).

Table 4.2

Means and Standard Deviations for Statistics Achievement By Year of Study of the Respondents

Participants' Year of Study	*n*	*M*	*SD*
1	5	80.8	7.86
2	11	67.91	12.14
3	14	69.14	12.97
4	21	70.05	15.13

An ANOVA was conducted to investigate whether there was any statistically significant mean difference of statistics achievement for participants' different years of study. In addition to the significance test, the strength of the effect size was calculated. The result of the ANOVA revealed no statistically significant mean differences of statistics achievement for different years of study of the participants ($F(3, 47) = 1.54$, $p > 0.05$). Furthermore, when the strength of the association was investigated, the value of the effect size was small, $\eta^2 = 0.09$, which means that students' year of study accounted for 9% of the variation in their statistics achievement.

4.7 Statistics Outcomes

In the Statistics Attitudes-Outcomes Model (Emmioglu, 2011), statistics outcomes include measurements for three variables. These variables were students' statistics achievement (on a scale of 1 = " DD" to 7 = "AA") by the end of their introductory statistics course, their willingness to use statistics in the remainder of their degree programs (on a scale of 1 = "not at all" to 7 = "great deal") and their willingness to use statistics when they are employed (on a scale of 1 = "not at all" to 7 = "great deal").

In the current study, as with Emmioglu's (2011) approach to rescaling students' statistics course achievement, the participating students' final course grades were rescaled as 1 (very poor) to 7 (very well). The final course grades of 50 or less were assigned the value of 1; final course grades between 51 and 60 were assigned the value of 2; final course grades between 61 and 65 were assigned the value of 3; final course grades between 66 and 70 were assigned the value of 4; final course grades between 71 and 75 were assigned the value of 5; final course grades between 76 and 80 were assigned the value of 6; and final course grades of 81 and above were assigned the value of 7.

Emmioglu (2011) confirmed that the three variables of students' statistics achievement by the end of their introductory statistics course and their self-ratings of their willingness to use statistics in the future (in the remainder of their degree program and in their future employment) reflect the component of Statistics Outcomes, which had a high factor determinacy value of 0.91. Therefore, for each participant in the current study a composite score on a scale of 1 to 7 was calculated as their statistics outcomes. This composite score was based on summing the three values (the rescaled statistics achievement, responses to willingness to use statistics in the remainder of the degree program and in future employment) and then taking the average of these three values. High composite scores on a scale of 1 to 7 reflect positive statistics outcomes. For all of the participants (n = 51), statistics outcomes had mean 4.03 and standard deviation of 1.28, which means that, on average, students had average statistics outcomes.

4.7.1 Statistics Outcomes by Sex of the Respondents

Statistics outcomes were examined by the sex of the respondents. The male participants had average statistics outcomes (n = 19, M = 4.04, SD = 1.34), which were similar to the female participants' statistics outcomes (n = 32, M = 4.02, SD = 1.27). The independent t-test showed no statistically significant mean difference between male and female participants' statistics outcomes ($t(49) = 0.04$, $p > 0.05$). The result of the t-test suggests that the mean difference between male and female participants' statistics outcomes was negligible.

4.7.2 Statistics Outcomes by Year of Study of the Respondents

Statistics outcomes were examined by the year of study of the participants. Table 4.3, on page 84, summarizes the means and standard deviations for statistics outcomes by the year of study of the participants. The first-year (n = 5) participants had the highest statistics outcomes (M = 5.13, SD = 1.07). Moreover, first-year and second-year participants had high statistics outcomes with their means above the mid-point value of 4 on a scale of 1 to 7 (Table 4.3). This result suggests that first-year and second-year students had high statistics achievement and high willingness to use statistics in the remainder of their degree program and in their future employment. However, third-year and fourth-year participants had somewhat low statistics outcomes with their means below the midpoint value of 4 (Table 4.3). This result suggests that third-year and fourth-year students had somewhat low statistics achievement and had somewhat low willingness to use statistics in the future (e.g., after they leave their statistics course).

Table 4.3

Means and Standard Deviations for Statistics Outcomes By Year of Study of the Respondents

Participants' Year of Study	*n*	*M*	*SD*
1	5	5.13	1.07
2	11	4.33	1.11
3	14	3.52	1.21
4	21	3.92	1.35

Additionally, an ANOVA was conducted to investigate whether there was any statistically significant mean difference of statistics outcomes for different years of study of the participants. In addition to the significance test, the strength of the effect size was calculated. The result of the ANOVA revealed no statistically significant mean differences of statistics outcomes for different years of study of the participants ($F(3, 47) = 2.38$, $p > 0.05$). Moreover, when the strength of the association was investigated, the value of the effect size was small, $\eta^2 = 0.13$, which means that students' year of study accounted for 13% of the variation in their statistics outcomes.

4.8 Students' Attitudes Toward Statistics

In the current study, SATS-36© was used to assess students' attitudes about statistics at both times in the semester, once at the beginning and another time at the end of the course (Schau, 2003b). Responses to each item on SATS-36© ranged from 1 (strongly disagree), through 4 (neither agree nor disagree) to 7 (strongly agree). Students' responses to the negatively worded items were reversed to reflect more positive agreement to that statement. Afterwards, responses to items in each of the six attitudes components of Affect, Cognitive Competence, Value, Difficulty, Interest, and Effort were summed and were divided by the number of items in that component. Table 4.4 presents mean and standard deviation values for the six attitudes components at both times of the test administrations.

Table. 4.4

Means and Standard Deviations for Pre-test, Post-test, and Change Scores by Attitudes Component (n = 51)

	Pre-test		Post-test		Change	
Attitudes Component	*M*	*SD*	*M*	*SD*	*M*	*SD*
Affect	3.57	1.18	3.77	1.32	0.20	1.00
Cognitive Competence	4.33	1.13	4.39	1.51	0.06	0.91
Value	4.92	1.05	4.64	1.10	-0.28*	0.95
Difficulty	3.21	0.72	3.37	0.87	0.16	0.72
Interest	4.77	1.37	4.35	1.51	-0.42*	1.24
Effort	6.34	1.00	5.88	0.90	-0.46*	1.22

*$p<0.05$

As presented in Table 4.4, students had positive attitudes in terms of Cognitive Competence, Value, Interest, and Effort for both the pre- and post-test. However, they had somewhat negative attitudes in terms of Affect, and Difficulty. At the beginning of their introductory statistics course, students somewhat disliked statistics. They believed that they were somewhat capable in applying their knowledge and skills in doing statistics. They somewhat valued the subject of statistics (they perceived it as a useful, relevant, and worthwhile subject) in their personal and professional lives. They believed that statistics was not going to be an easy subject. They were somewhat interested in statistics. They reported that they planned to spend a great deal of effort on learning statistics.

Although students' feelings concerning statistics, their perception of applying their knowledge and skills in doing statistics, and their perception of statistics as less of a difficult subject increased by the end of their introductory statistics course, they still somewhat disliked statistics and perceived it as a difficult subject. They still valued the subject of statistics at the end of their statistics course; however, they perceived it as a slightly less important subject for their personal and professional lives. They were still somewhat interested in statistics; however, they reported being less interested in statistics by the end of their statistics course. They still reported spending lots of effort on learning statistics, but less than what they had planned to spend at the beginning of their statistics course.

In addition to the descriptive statistical analyses for comparing pre- and post-test scores in each of the attitudes component, t-tests were conducted to assess whether mean gain-scores, that is pre-test subtracted from post-test scores, were statistically significant from zero. In the Affect, Cognitive Competence, and Difficulty attitudes components, mean gain-scores were not statistically significantly different from zero ($p > 0.05$). This means there was no evidence that students' feeling concerning statistics, their perception regarding their capability in applying their skills and knowledge in doing statistics, and their perception of the difficulty of the subject of statistics changed from the beginning to the end of their introductory statistics course.

In the Value, Interest, and Effort attitudes components, the mean gain-scores were statistically significantly different from zero ($p < 0.05$). This means that there was evidence that students' perception regarding the value (usefulness, relevance, and worth) of the subject of statistics in their personal and professional lives, their interest in statistics, and their planned effort to spend time learning statistics negatively changed from the beginning to the end of their introductory statistics course.

Schau and Emmioglu (2012), and Millar and Schau (2010) assert that a practical difference in terms of a change in students' attitudes from the beginning to the end of their introductory statistics course should be a value of at least 0.50 on a 7-point Likert scale. For the current study, changes in students' attitudes toward statistics from pre-test to post-test in each of the attitudes component were less than 0.50 difference on a 7-point Likert scale to be considered as a practical significance. Therefore, it could thus be suggested that, in all attitudes components, there were no practical significances in terms of changes to students' attitudes toward statistics from the beginning to the end of their introductory statistics course.

4.8.1 Attitudes Toward Statistics by Sex of the Respondents

Students' attitudes toward statistics were examined by sex and during both times of the test administration, once at the beginning and another time at the end of the introductory statistics course under study. Table 4.5 presents means and standard deviations for the six attitudes components at both times of the test administration (pre-test and post-test) for both male (n = 19) and female (n = 32) respondents.

Table. 4.5

Means and Standard Deviations for Pre-test, and Post-test Scores by Attitudes Component and Sex of the Respondents

	Pre-test		Post-test	
	Male n = 19	Female n = 32	Male n = 19	Female n = 32
Attitudes Component	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
Affect	3.94 (1.10)	3.35 (1.19)	3.93 (1.17)	3.67 (1.41)
Cognitive Competence	4.57 (1.10)	4.19 (1.14)	4.58 (1.10)	4.27 (1.19)
Value	5.12 (1.10)	4.79 (1.01)	4.73 (1.05)	4.59 (1.15)
Difficulty	3.06 (0.75)	3.30 (0.70)	3.19 (0.80)	3.48 (0.89)
Interest	4.83 (1.53)	4.74 (1.29)	4.20 (1.67)	4.44 (1.43)
Effort	6.49 (0.76)	6.26 (1.12)	5.87 (0.93)	5.89 (0.90)

In terms of the Affect component, both male and female students reported somewhat negative feelings concerning statistics at both times of the test administration. They both somewhat disliked the subject of statistics. On average, male students' feelings concerning statistics remained the same from the beginning to the end of their introductory statistics course.

They reported higher Affect attitude scores than the female students at both times of the test administration. On average, female students' feelings concerning statistics slightly increased by the end of their statistics course; however, they still reported disliking statistics.

In terms of the Cognitive Competence component, both male and female students reported somewhat positive attitudes at both times of the test administration. They both somewhat perceived themselves as capable of applying their skills and knowledge in doing statistics. On average, male students' perception regarding their capability in doing statistics remained the same from the beginning to the end of their introductory statistics course. They reported higher Cognitive Competence attitudes scores than the female students at both times. On average, female students' perception regarding their capability in applying their skill and knowledge in doing statistics slightly increased by the end of their introductory statistics course.

In terms of the Value component, both male and female students reported somewhat positive attitudes at both times of the test administration. They both perceived statistics as a valuable, useful, and relevant subject in their personal and professional lives. On average, male students reported higher Value attitudes scores than the females at both times, which means that they tended to value the subject of statistics more than the females. However, both male and female students reported that they valued the subject of statistics less by the end of their statistics course.

In terms of the Difficulty component, both male and female students reported somewhat negative attitudes at both times of the test administration. They both perceived statistics as a somewhat difficult subject. On average, male students reported lower Difficulty attitudes scores than the females at both times, which means they perceived the subject of statistics as more difficult than the females. By the end of their introductory statistics course, both male and female students reported higher Difficulty attitudes scores than what they had reported initially in the term, which means that they both perceived statistics as a less difficult subject.

In terms of the Interest component, both male and female students reported somewhat positive attitudes at both times of the test administration. They both indicated that they were somewhat interested in statistics. On average, male students indicated higher Interest attitude scores than the female students at the beginning of their introductory statistics course. For both male and female students, their interest in statistics dropped by the end of their statistics course, which indicates that they were both less interested in statistics. Male students indicated the largest drop in their Interest attitude scores.

In terms of the Effort component, both male and female students reported high positive attitudes at both times of the test administration. They both reported that they expected to spend and to invest lots of time in learning statistics. On average, male students indicated higher Effort attitude scores than the females at the beginning of their introductory statistics course. Both male and female students reported similar Effort attitudes scores by the end of their introductory statistic course; however, their scores regarding the amount of time they spent to learn statistics dropped by the end of their statistics course.

In addition to the descriptive statistical analyses, mixed-design ANOVA were conducted to examine whether male or female participants had different levels of attitudes toward statistics at different times of the test administration. The sex of the respondents was treated as the between-subject factor, and the time of test administration was treated as the within-subject factor. Since multiple significance tests were applied, the alpha-level was adjusted to 0.001 to control for the Type I error rate, which occurs when a statistical test rejects a true null hypothesis (Kutner et al., 2005).

The results of the mixed-design ANOVA showed no statistically significant mean differences between male and female participants' attitudes towards statistics for different times of the test administration. Moreover, adjusting for the time of the test administration, there were no statistically significant mean differences between male and female participants' attitudes toward statistics. These results suggest that the sex of the students did not significantly contribute to explaining the variations in their attitudes toward statistics.

4.8.2 Attitudes Toward Statistics by Year of Study of the Respondents

Students' attitudes toward statistics were examined by the year of their study at both times of the test administration. Table 4.6, on page 93, presents means and standard deviations for the six attitudes components at both times of the test administration (pre-test and post-test) for first year (n = 5), second year (n = 11), third year (n = 14), and fourth year (n = 21) students.

In terms of the Affect component, first year students indicated positive feelings concerning statistics at the beginning of their introductory statistics course. However, second, third, and fourth year students reported that they somewhat disliked statistics. By the end of their introductory statistics course, first year students still reported the highest and the most improved positive attitudes concerning their feelings toward statistics. Second year students also showed improvement and reported positive feelings concerning statistics, but not as much as the first year students. Although third year students reported higher scores than they did initially at the beginning of their statistics course, they still had somewhat negative feelings concerning statistics. Among all the participants, fourth year students were the only group whose scores slightly dropped in the Affect component. They reported that they somewhat disliked statistics more by the end of their introductory statistics.

In terms of the Cognitive Competence component, all students perceived themselves as capable in applying their skills and knowledge to doing statistics both at the beginning and at the end of their introductory statistics course. First year students reported the highest Cognitive Competence attitude scores at both times of the test administration. By the end of their introductory statistics course, first, second, and fourth year students reported higher Cognitive Competence attitude scores than what they initially reported in the term.

In terms of the Value component, all students tended to value the subject of statistics (viewed it as useful, relevant, and worthwhile) in their personal and professional lives, both at the beginning and at the end of their introductory statistics course. However, all of the students tended to value the subject of statistics less by the end of their introductory statistics course. At both times of the test administration, first year students tended to believe that the subject of statistics was more valuable in their personal and professional lives than all other students.

In terms of the Difficulty component, only first year students perceived the subject of statistics as neither easy nor difficult by the end their introductory statistics course. All of the remaining participants perceived the subject of statistics as somewhat difficult, both at the beginning and at the end of their introductory statistics course. Although second, third, and fourth year students tended to report that they perceived the subject of statistics as less difficult by the end of their introductory statistics course, their average Difficulty attitude scores were still below the mid-point value of 4 on a 7-point Likert scale. That means, except for first year students, those in the second, third, and fourth years of their study still perceived the subject of statistics as somewhat difficult by the end of their introductory statistics course.

In terms of the Interest component, all students reported that they were interested in statistics, both at the beginning and at the end of their introductory statistics course. However, all students indicated that they were less interested in statistics by the end of their introductory statistics course. First year students indicated the highest Interest attitude scores out of all other students at both times of test administration. That means that first year students were more likely to be interested in statistics than all of the other students.

In terms of the Effort component, all students reported that they planned to spend lots of time and effort to learn statistics at the beginning of their introductory statistics course. Although their Effort attitude scores remained high by the end of the course, all students reported that they spent less time than what they had initially planned during the term to learn statistics. First year students indicated the highest Effort attitude scores out of all other students at both times of test administration. That means that first year students were more likely to plan to invest their time in learning statistics than all of the other students.

In addition to the descriptive statistical analyses, mixed-design ANOVA were conducted to examine whether students in different years of study had different levels of attitudes toward statistics at different times of the test administration. The participating students' year of study was treated as the between-subject factor, and the time of test administration was treated as the within-subject factor. Since multiple significance tests were conducted, the significance alpha-level was adjusted to 0.001 to control for the Type I error rate, which occurs when a statistical test rejects a true null hypothesis (Kutner et al., 2005).

The results of the mixed-design ANOVA showed no statistically significant mean differences of attitudes toward statistics among students in different years of study at different times of the test administration. Moreover, adjusting for the time of the test administration, there were no statistically significant mean differences of attitudes toward statistics among students in different years of study. These results suggest that students in different years of study did not significantly contribute to explaining the variations in their attitudes toward statistics at either time of test administration.

Table 4.6

Means and Standard Deviations for Pre-test, and Post-test Scores by Attitudes Component and by Year of Study of the Respondents

			Pre-test		Post-test	
Attitudes Component	Year of Study	n	*M*	*SD*	*M*	*SD*
Affect						
	1st Year	5	4.86	0.96	5.43	0.52
	2nd Year	11	3.88	1.40	4.20	1.34
	3rd Year	14	3.21	1.21	3.55	1.08
	4th Year	21	3.34	0.86	3.29	1.26
Cognitive Competence						
	1st Year	5	5.53	0.84	5.60	0.58
	2nd Year	11	4.41	1.17	4.74	1.09
	3rd Year	14	4.28	1.07	4.14	1.04
	4th Year	21	4.04	1.08	4.08	1.17
Value						
	1st Year	5	5.42	1.05	4.96	0.82
	2nd Year	11	5.01	0.85	4.88	1.18
	3rd Year	14	4.93	1.11	4.42	0.82
	4th Year	21	4.75	1.21	4.59	1.30
Difficulty						
	1st Year	5	3.66	0.26	4.03	0.67
	2nd Year	11	3.36	0.49	3.57	0.70
	3rd Year	14	3.37	0.89	3.35	0.69
	4th Year	21	2.92	0.70	3.12	1.02
Interest						
	1st Year	5	5.30	1.04	4.75	1.45
	2nd Year	11	5.03	1.05	4.59	1.62
	3rd Year	14	4.89	1.18	4.21	1.42
	4th Year	21	4.43	1.67	4.23	1.61
Effort						
	1st Year	5	6.50	0.98	6.24	0.63
	2nd Year	11	6.34	0.77	6.07	0.87
	3rd Year	14	6.05	1.59	5.39	0.93
	4th Year	21	6.50	0.53	6.02	0.88

4.9 Correlations Among Variables

To estimate correlations among the variables in the current study, Pearson correlations were calculated. For determining the strength of the correlations, the criterion described by Field (2009), and Levin, Fox, and Forde (2014) was adopted for the current study. That is, correlation coefficients of less than 0.10 were considered weak correlations, between 0.10 and less than 0.30 were considered weak to moderate correlations, between 0.30 and less than 0.50 were considered moderate to high correlations, and 0.50 and higher were considered strong correlations. Next, I will describe correlations among pre-attitudes component scores, post-attitudes component scores, and pre- and post-attitudes component scores.

4.9.1 Correlations Among Pre-scores

Table 4.7 presents the Pearson correlations among the pre-attitudes components of Affect, Cognitive Competence, Value, Difficulty, Interest, Effort, and participants' past mathematics achievement.

Table 4.7

Correlations Among Pre-scores by Attitudes Component and Past Math Achievement

Pre-scores	1	2	3	4	5	6	7
1. Affect	1						
2. Cognitive Competence	0.82*	1					
3. Value	0.43*	0.56*	1				
4. Difficulty	0.48*	0.48*	0.09	1			
5. Interest	0.48*	0.38*	0.56*	0.15	1		
6. Effort	-0.11	0.004	0.41*	-0.45*	0.26	1	
7. Past Math Achievement	0.53*	0.53*	0.47*	0.19	0.24	-0.19	1

*$p<0.05$

There were strong, positive, statistically significant correlations between Affect and Cognitive Competence, Cognitive Competence and Value, and Value and Interest attitudes components (Table 4.7). The results show that, at the beginning of their introductory statistics course, students who felt capable in applying their skills and knowledge while doing statistics, reported liking statistics, and tended to value the subject (viewed it as useful, relevant, and worthwhile) in their personal and professional lives. Students who valued the subject of statistics reported that they were interested in statistics.

There were moderate to strong, positive, statistically significant correlations between Affect and Value, Affect and Difficulty, Affect and Interest, Cognitive Competence and Difficulty, Cognitive Competence and Interest, and Value and Effort attitudes components (Table 4.7). There was a moderate to strong, negative, statistically significant correlation between Difficulty and Effort attitudes components. The results show that, at the beginning of their introductory statistics course, students who reported liking statistics also valued the subject, perceived the subject as less difficult, and were interested in statistics. Students who felt capable in applying their skills and knowledge in doing statistics also reported perceiving the subject as less difficult, and were interested in statistics. Students who valued the subject (viewed it as useful, relevant, and worthwhile) in their personal and professional lives reported planning to spend more time in learning statistics. However, students who perceived the subject of statistics as less difficult reported that they planned to spend less time learning statistics.

As presented in Table 4.7, there were weak, non-statistically significant correlations between Affect and Effort, Cognitive Competence and Effort, Interest and Effort, Difficulty and Value, and Difficulty and Interest attitudes components. These results suggest that, at the beginning of their introductory statistics course, there was no evidence that students' effort to learn statistics was associated with their feelings concerning statistics, with their perceptions of their capability in applying their knowledge and skills in doing statistics, and with their interest in statistics. Moreover, there was no evidence that students' perception of the difficulty of statistics as a subject was associated with how they valued the subject in their personal and professional lives, and with their interest in statistics.

Participants' past mathematics achievement had strong, positive, statistically significant correlations with the Affect and Cognitive Competence attitudes components (Table 4.7). These results show that, at the beginning of their introductory statistics course, students who reported doing well in their past mathematics courses also reported liking the subject of statistics, and reported being capable in applying their skills and knowledge in doing statistics. Participants' past mathematics achievement had moderate to strong, positive, statistically significant correlation with the Value component (Table 4.7). This result indicates that, at the beginning of their introductory statistics course, students who reported doing well in their past mathematics courses also valued the subject of statistics in their personal and professional lives.

Participants' past mathematics achievement had weak, non-statistically significant correlations with the Difficulty, Interest, and Effort attitudes components (Table 4.7). These results suggest that, at the beginning of their introductory statistics course, there was no evidence that students' past mathematics achievement was associated with their perceptions of the difficulty of, their interest in, and their planned effort to learn statistics.

4.9.2 Correlations Among Pre- and Post-scores

Table 4.8, on page 97, presents the Pearson correlations among the pre- and post-attitudes components of Affect, Cognitive Competence, Value, Difficulty, Interest, Effort, and participants' past mathematics achievement, their statistics course grade, and their statistics outcomes.

Table 4.8

Correlations Among Pre- and Post-scores by Attitudes Component, Past Math Achievement, Statistics Course Grade, and Statistics Outcomes

	Pre-scores						
Post-scores	1	2	3	4	5	6	Past Math Achievement
1. Affect	0.68*	0.60*	0.49*	0.45*	0.52*	-0.07	0.43*
2. Cognitive Competence	0.62*	0.68*	0.56*	0.42*	0.48*	0.01	0.42*
3. Value	0.32*	0.39*	0.61*	0.24	0.42*	0.12	0.15
4. Difficulty	0.41*	0.46*	0.29	0.60*	0.26	-0.07	0.20
5. Interest	0.38*	0.33*	0.41*	0.21	0.64*	-0.00	0.32*
6. Effort	0.06	-0.06	-0.03	-0.21	-0.04	0.18	0.07
7. Statistics Course Grade	0.23	0.21	0.22	-0.03	0.13	0.12	0.34*
8. Statistics Outcomes	0.50*	0.41*	0.43*	0.24	0.48*	0.06	0.54*

*$p<0.05$

Post-scores in the Affect attitudes component had strong, positive, statistically significant correlations with pre-scores in the Affect, Cognitive Competence, and Interest attitudes components (Table 4.8). The results show that students who tended to like statistics felt capable in applying their skills and knowledge in doing statistics, and were interested in statistics at the beginning of their introductory statistics course; they still liked statistics by the end of their introductory statistics course. Post-scores in the Affect attitudes component had moderate to strong, positive, statistically significant correlations with pre-scores in the Value and Difficulty attitudes components (Table 4.8). The results show that students who tended to value the subject of statistics in their personal and professional life, and perceived the subject of statistics as less difficult at the beginning of their introductory statistics course, still tended to like statistics by the end of their introductory statistics course.

There was a weak, non-statistically significant correlation between post-scores in the Affect and pre-scores in the Effort attitudes component (Table 4.8). These results suggest that there was no evidence that students' planned effort to spend time learning statistics at the beginning of their introductory statistics course was related to their feelings concerning statistics by the end of their introductory statistics course.

Post-scores in the Cognitive Competence attitudes component had strong, positive, statistically significant correlations with pre-scores in the Affect, Cognitive Competence, and Value attitudes components (Table 4.8). The results show that students who reported liking statistics, felt capable in applying their skills and knowledge in doing statistics, and valued the subject in their personal and professional lives at the beginning of their introductory statistics course, still felt capable in applying their skills and knowledge in doing statistics by the end of their introductory statistics course.

Post-scores in the Cognitive Competence attitudes component had moderate to strong, positive, statistically significant correlations with the pre-scores in the Difficulty and Interest attitudes components (Table 4.8). The results show that those students who perceived the subject of statistics as less difficult, and were interested in statistics at the beginning of their introductory statistics course, felt capable in applying their skills and knowledge in doing statistics by the end of their introductory statistics course. Post-scores in the Cognitive Competence component had weak, non-statistically significant correlation with the pre-scores in the Effort attitudes component (Table 4.8). These results suggest that there was no evidence that students' planned effort to spend time learning statistics at the beginning of their introductory statistics course was related to their perception of their capability in applying their skills and knowledge in doing statistics by the end of their introductory statistics course.

Post-scores in the Value attitudes component had strong, positive, statistically significant correlation with pre-scores in the Value attitudes component (Table 4.8). The results show that students who tended to value the subject of statistics in their personal and professional lives at the beginning of their introductory statistics course still valued the subject of statistics by the end of their introductory statistics course. Post-scores in the Value attitudes component had moderate to strong, positive, statistically significant correlations with the pre-scores in the Affect, Cognitive Competence, and Interest attitudes components (Table 4.8). The results show that students who tended to like statistics, felt capable in applying their skills and knowledge in doing statistics, and were interested in statistics at the beginning of their introductory statistics course, tended to value the subject of statistics in their personal and professional lives by the end of their introductory statistics course.

Post-scores in the Value attitudes component had weak, non-statistically significant correlations with pre-scores in the Difficulty and Effort attitudes components (Table 4.8). These results suggest that there was no evidence that students' perception of statistics as a difficult subject and their planned effort to spend time learning statistics at the beginning of their introductory statistics course were related to how they valued the subject of statistics in their personal and professional lives by the end of their introductory statistics course.

Post-scores in the Difficulty attitudes component had strong, positive, statistically significant correlation with pre-scores in the Difficulty attitudes component (Table 4.8). The results show that students who perceived the subject of statistics as less difficult at the beginning of their introductory statistics course still perceived the subject as less difficult by the end of their introductory statistics course. Post-scores in the Difficulty attitudes component had moderate to strong, positive, statistically significant correlations with the pre-scores in the Affect and Cognitive Competence attitudes components (Table 4.8). The results show that students who tended to like statistics and felt capable in applying their skills and knowledge in doing statistics at the beginning of their introductory statistics course tended to perceive the subject of statistics as less difficult by the end of their introductory statistics course.

Post-scores in the Difficulty attitudes component had weak, non-statistically significant correlations with pre-scores in the Value, Interest and Effort attitudes components (Table 4.8). These results suggest that there was no evidence that students' perception about the value of the subject of statistics in their personal and professional lives, their interest in statistics, and their planned effort to spend time learning statistics at the beginning of their introductory statistics course were related to how they perceived statistics as a less difficult subject by the end of their introductory statistics course.

Post-scores in the Interest attitudes component had strong, positive, statistically significant correlation with pre-scores in the Interest attitudes component (Table 4.8). The results show that students who were interested in statistics at the beginning of their introductory statistics course were still interested in statistics by the end of their introductory statistics course. Post-scores in the Interest attitudes component had moderate to strong, positive, statistically significant correlations with the pre-scores in the Affect, Cognitive Competence, and Value attitudes components (Table 4.8). The results show that students who tended to like statistics, felt capable in applying their skills and knowledge in doing statistics, and valued the subject in their personal and professional lives at the beginning of their introductory statistics course, were interested in statistics by the end of their introductory statistics course.

Post-scores in the Interest attitudes component had weak, non-statistically significant correlations with pre-scores in the Difficulty and Effort attitudes components (Table 4.8). These results suggest that there was no evidence that students' perception about the difficulty of the subject of statistics, and their planned effort to spend time learning statistics at the beginning of their introductory statistics course were related to their interest in statistics by the end of their introductory statistics course.

Post-scores in the Effort attitudes component had weak, non-statistically significant correlations with all of the pre-attitudes components scores (Table 4.8). There was no evidence that students' feelings concerning statistics, their perceptions regarding their capability in doing statistics, their valuing of the subject, their perception of the difficulty of the subject of statistics, their interest in statistics, and their planned effort to spend time learning statistics at the beginning of their introductory statistics course were related to their reported amount of effort spent learning statistics by the end of their introductory statistics course.

Participants' past mathematics achievement had moderate to strong, positive, statistically significant correlations with their post-scores in the Affect, Cognitive Competence, and Interest attitudes components (Table 4.8). These results indicate that students who reported doing well in their past mathematics courses tended to like statistics, felt capable in applying their skills and knowledge in doing statistics, and were interested in statistics by the end of their introductory statistics course. Students' past mathematics achievement had weak, non-statistically significant correlations with their post-scores in the Value, Difficulty, and Effort attitudes components (Table 4.8). These results indicate that there was no evidence that students' past mathematics achievement was related to their perceptions regarding the value of and the difficulty of the subject of statistics, and their reported amount of effort spent learning statistics by the end of their introductory statistics course.

Statistics course grades had moderate to strong, positive, statistically significant correlation with participants' past mathematics achievement (Table 4.8). This result indicates that students who reported doing well in their past mathematics courses had high statistics course grades by the end of their introductory statistics course. Statistics course grades had weak, non-statistically significant correlations with the pre-attitudes components scores (Table 4.8). There was no evidence that students' feelings concerning statistics, their perception regarding their capability in doing statistics, their perceptions about the value of the subject, their views about the difficulty of the subject of statistics, their interest in statistics, and their planned effort to spend time learning statistics at the beginning of their introductory statistics course were related to their statistics course grades by the end of their course.

Statistics outcomes were a composite mean score that was calculated by taking the average of three variables in the current study. These variables were participants' statistics course grade, their willingness to use statistics in the remainder of their degree program, and their willingness to use statistics in their future employment. Statistics course grade and statistics outcomes had strong, statistically significant and positive correlation ($r = 0.68$, $p < 0.0001$). This means that students who had high statistics course grades also had high statistics outcomes by the end of their introductory statistics course.

Statistics outcomes had strong, positive, statistically significant correlations with the pre-scores in the Affect attitudes component, and with participants' past mathematics achievement (Table 4.8). These results indicate that students who reported liking statistics and reported doing well in their past mathematics courses at the beginning of their introductory statistics course had high statistics outcomes by the end of their introductory statistics course. Statistics outcomes had moderate to strong, positive, statistically significant correlations with the pre-scores in the Cognitive Competence, Value, and Interest attitudes components (Table 4.8). These results indicate that students who felt capable in applying their skills and knowledge while doing statistics, valued the subject of statistics in their personal and professional lives, and were interested in statistics at the beginning of their introductory statistics course had high statistics outcomes by the end of their introductory statistics course.

Statistics outcomes had weak, non-statistically significant correlations with the pre-scores in the Difficulty and Effort attitudes components (Table 4.8). There was no evidence that students' perception of the difficulty of the subject of statistics and their planned effort to spend time learning statistics at the beginning of their introductory statistics course were related to their statistics outcomes by the end of their introductory statistics course.

4.9.3 Correlations Among Post-scores

Table 4.9 presents the Pearson correlations among the post-attitudes components of Affect, Cognitive Competence, Value, Difficulty, Interest, Effort, and students' statistics course grade, and their statistics outcomes.

Table 4.9

Correlations Among Post-scores by Attitudes Component, Statistics Course Grade, and Statistics Outcomes

Post-scores	1	2	3	4	5	6
1. Affect	1					
2. Cognitive Competence	0.88*	1				
3. Value	0.50*	0.57*	1			
4. Difficulty	0.60*	0.56*	0.23	1		
5. Interest	0.46*	0.45*	0.68*	0.17	1	
6. Effort	-0.05	0.01	0.12	-0.36*	0.32*	1
7. Statistics Course Grade	0.30*	0.40*	0.18	-0.10	0.17	0.28*
8. Statistics Outcomes	0.55*	0.60*	0.55*	0.14	0.64*	0.37*

*p<0.05

There were strong, positive, statistically significant correlations between Affect and Cognitive Competence, Affect and Value, Affect and Difficulty, Cognitive Competence and Value, Cognitive Competence and Difficulty, and Value and Interest attitudes components

(Table 4.9). The results show that, by the end of their introductory statistics course, students who reported liking statistics also felt capable in applying their skills and knowledge in doing statistics, valued the subject in their personal and professional lives, and perceived the subject as less difficult. Students who felt capable in applying their skills and knowledge in doing statistics reported that they valued the subject in their personal and professional lives, and perceived the subject of statistics as less difficult. Students who valued the subject of statistics reported that they were interested in statistics.

There were moderate to strong, positive, statistically significant correlations between Affect and Interest, Cognitive Competence and Interest, and Interest and Effort attitudes components (Table 4.9). The results show that, by the end of their introductory statistics course, students who were interested in statistics reported that they liked statistics, felt capable in applying their skills and knowledge in doing statistics, and reported that they spent a great deal of effort in learning statistics. There was a moderate, negative, statistically significant correlation between Difficulty and Effort attitudes components (Table 4.9). This means that, by the end of their introductory statistics course, those students who perceived the subject of statistics as less difficult reported that they spent less time in learning statistics.

Effort attitudes component had weak, non-statistically significant correlations with Affect, Cognitive Competence, and Value attitudes components (Table 4.9). There was no evidence that, by the end of their introductory statistics course, students' feelings concerning statistics, their perceptions of their capability in doing statistics, and how they tended to value the subject of statistics were related to their effort to learn statistics. Difficulty attitudes component had weak, non-statistically significant correlations with Value and Interest attitudes components (Table 4.9). There was no evidence that, by the end of their introductory statistics course, students' perception regarding how they tended to value the subject of statistics and their interest in statistics were related to how they perceived statistics as a difficult subject.

Statistics course grade had moderate, positive, statistically significant correlations with Affect, Cognitive Competence, and Effort attitudes components (Table 4.9). These results indicate that, by the end of their introductory statistics course, students who liked statistics, felt capable in applying their skills and knowledge in doing statistics, and reported expending lots of effort in learning statistics had high statistics course grades. Statistics course grade had weak, non-statistically significant correlations with Value, Difficulty and Interest attitudes components (Table 4.9). By the end of their introductory statistics course, there was no evidence that students' perceptions in regards to how they valued the subject of statistics, their perceptions about the difficulty of the subject, and their interest in statistics were related to their statistics course grade.

Statistics outcomes had strong, positive, statistically significant correlations with Affect, Cognitive Competence, Value, and Interest attitudes components (Table 4.9). These results indicate that, by the end of their introductory statistics course, students who liked statistics, felt capable in applying their skills and knowledge in doing statistics, valued the subject in their personal and professional lives, and were interested in statistics had high statistics outcomes. There was a moderate, positive, statistically significant correlation between statistics outcomes and Effort attitudes component (Table 4.9). This means that students who reported spending lots of effort in learning statistics had high statistics outcomes by the end of their introductory statistics course. There was a weak, non-statistically significant correlation between statistics outcomes and Difficulty attitudes component (Table 4.9). There was no evidence that students' perception regarding the difficulty of the subject was related to their statistics outcomes by the end of their introductory statistics course.

4.9.4 Correlations with the Gain-scores

In this section, for each attitudes-component, I describe participants' gain-scores' (their pre-scores subtracted from their post-scores) correlations with their corresponding pre-scores, their past mathematics achievement, their statistics course grade, and their statistics outcomes. The results of the Pearson correlation analysis indicated that gain-scores in each of the attitudes component had moderate, negative, statistically significant correlation with their corresponding pre-scores in that attitudes-component.

Gain-scores in the Affect component had moderate, negative, statistically significant correlation with its pre-scores (r = -0.28, $p < 0.05$). Students who reported liking statistics more at the beginning of their introductory statistics course changed their feeling concerning statistics negatively from the beginning to the end of their introductory statistics course.

Gain-scores in the Cognitive Competence attitudes component had moderate, negative, statistically significant correlation with its pre-scores (r = -0.38, $p < 0.05$). Students who felt more capable in doing statistics at the beginning of their introductory statistics course changed their perception regarding their capability of doing statistics negatively from the beginning to the end of their introductory statistics course.

Gain-scores in the Value component had moderate, negative, statistically significant correlation with its pre-scores (r = -0.39, $p < 0.05$). Students who valued the subject (viewed it as useful, relevant, and worthwhile) in their personal and professional lives more at the beginning of their introductory statistics course changed their perception of statistics as a valuable subject negatively from the beginning to the end of their introductory statistics course.

Gain-scores in the Difficulty attitudes component had moderate, negative, statistically significant correlation with its pre-scores (r = -0.29, $p < 0.05$). Students who perceived the subject of statistics as easy rather than difficult at the beginning of their introductory statistics course changed their perception of easiness of the subject of statistics negatively from the beginning to the end of their introductory statistics course.

Gain-scores in the Interest attitudes component had moderate, negative, statistically significant correlation with its pre-scores (r = -0.33, $p < 0.05$). Students who were interested in statistics at the beginning of their introductory statistics course changed their interest in statistics negatively from the beginning to the end of their introductory statistics course.

Gain-scores in the Effort attitudes component had high, negative, statistically significant correlation with its pre-scores (r = -0.69, $p < 0.05$). Students who planned to spend a great deal of effort learning statistics at the beginning of their introductory statistics course changed their planned effort to learn statistics negatively from the beginning to the end of their introductory statistics course.

Gain-scores in all of the six attitudes components had weak, non-statistically significant correlations with past mathematics achievement, statistics course grade, and statistics outcomes at the end of the introductory statistics course under this study. These results suggested that there was no evidence that students' past mathematics achievement, their statistics course grade, and their statistics outcomes were related to their changes in attitudes toward statistics in any of the six attitudes components from the beginning to the end of their introductory statistics course.

4.10 Linear Models

In the current study, the first research question aimed at investigating changes in students' attitudes toward statistics in the introductory statistics for the social sciences course.

Similar to Millar and Schau (2010), I used the Ordinary Least Squares (OLS) statistical method. Millar and Schau (2010) considered mean gained attitudes scores (subtracting pre-scores from post-scores) conditional on the pre-scores in each attitudes-component.

The second research question aimed at investigating the relationships between students' attitudes toward statistics and their sex, their year of study, their past mathematics achievement, and their statistics course grade. However, based on the preliminary statistical analyses described in this chapter (sections 4.8.1 and 4.8.2), it was found that neither the sex nor the year of study of the participants showed any statistically significant relationships with any of the attitudes components at either time of the test administrations. Moreover, as described in section 4.9.3, none of the gain-scores in any of the six attitudes components had statistically significant correlations with past mathematics achievement, and statistics course grade. Therefore, simple linear models were employed with only pre-scores as the predictor variable for gain-scores in each attitudes-component. That is, mean gain-scores in each attitudes-component were conditioned on its pre-scores.

Pre-scores in the Affect component were a statistically significant predictor of gain-scores in that component ($t(49) = -2.04$, $p < 0.05$). However, the coefficient of determination was low, $r^2 = 0.08$. That is, pre-scores in the Affect component explained about 8% of the variation in the gain-scores of that component. For a low pre-test score of 2, the conditional estimated mean gain was 0.57, with a 95% confidence interval of (0.11, 1.03). That means, on average, students' feelings concerning statistics with a low pre-score of 2 improved from pre-test to post-test; their feelings concerning statistics at the end of their introductory statistics course were more positive than what they reported at the beginning of their course.

However, as described earlier (section 4.8), on average, students did not have positive feelings concerning statistics by the end of their introductory statistics course, even though their pretest scores increased by about 0.57 (e.g., from 2 to 2.57 on a 7-point scale) from pre-test to post-test. For a high pretest score of 6, the conditional estimated mean gain was -0.38, with a 95% confidence interval of (-1.01, 0.25). Since the 95% confidence interval includes the value of zero in its range, it cannot be concluded that, on average, students' feelings concerning statistics for those with high pretest scores of 6 changed from the beginning to the end of the course. Thus, it is plausible to suggest that, for those students with high pre-test scores of 6 in the Affect component, their feelings concerning statistics did not change from pre-test to post-test.

Pre-scores in the Cognitive Competence component was a statistically significant predictor of the gain-scores in that component ($t(49)$ = -2.84, $p < 0.05$). The coefficient of determination was somewhat low, $r^2 = 0.14$. That is, pre-scores in the Cognitive Competence component explained about 14% of the variation in the gain-scores of that component. For a low pre-test score of 2, the conditional estimated mean gain was 0.76, with a 95% confidence interval of (0.21, 1.32). This means that, on average, students' perception regarding their capability in applying their skills and knowledge in doing statistics with low pre-score of 2 improved from pre-test to post-test; their perception regarding their capability in applying their skills and knowledge in doing statistics at the end of their introductory statistics course was more positive than what they reported at the beginning of their course.

For a high pretest score of 6 in the Cognitive Competence component, the conditional estimated mean gain was -0.45, with a 95% confidence interval of (-0.88, -0.02). On average, students' perception regarding their capability in doing statistics for those with a high pretest score of 6 dropped from the beginning to the end of their introductory statistics course.

Pre-scores in the Value component was a statistically significant predictor of the gain-scores in that attitudes-component ($t(49)$ = -3.00, p < 0.05). The coefficient of determination was somewhat low, r^2 = 0.16. That is, pre-scores in the Value component explained about 16% of the variation in the gain-scores of that component. For a low pre-test score of 2, the conditional estimated mean gain was 0.77, with a 95% confidence interval of (0.02, 1.51). This means that, on average, students' perception regarding the value (usefulness, relevance, and worth) of the subject of statistics in their personal and professional lives with a low pre-score of 2 improved from pre-test to post-test; their perception regarding the value of the subject at the end of their introductory statistics course was more positive than what they reported at the beginning of their course.

For a high pretest score of 6 in the Value component, the conditional estimated mean gain was -0.67, with a 95% confidence interval of (-1.03, -0.31). On average, students' perception regarding the value (usefulness, relevance, and worth) of the subject for those with a high pretest score of 6 dropped from the beginning to the end of their introductory statistics course.

Pre-scores in the Difficulty component was a statistically significant predictor of the gain-scores in that component ($t(49)$ = -2.08, p < 0.05). The coefficient of determination was low, r^2 = 0.08. That is, pre-scores in the Difficulty component explained about 8% of the variation in the gain-scores of that component. For a low pre-test score of 2, the conditional estimated mean gain was 0.51, with a 95% confidence interval of (0.12, 0.89). This means, on average, students' perception regarding the easiness of the subject of statistics with a low pre-score of 2 improved from pre-test to post-test; their perception regarding the easiness of the subject of statistics at the end of their introductory statistics course was more positive than what they reported at the beginning of their course.

However, as noted earlier (section 4.8), on average, students did not perceive the subject of statistics as less difficult by the end of their course, even though their pretest scores increased by about 0.51 (e.g., from 2 to 2.51 on a 7-point scale) from pre-test to post-test. For a high pretest score of 6, the conditional estimated mean gain was -0.64, with a 95% confidence interval of (-1.43, 0.16). Since the 95% confidence interval includes the value of zero in its range, it cannot be concluded that, on average, students' perception regarding the easiness of the subject of statistics for those with a high pretest score of 6 dropped from the beginning to the end of the course. Therefore, it is plausible to suggest that, for those students with a high pre-test score of 6 in the Difficulty component, their perception regarding the easiness of the subject of statistics did not change from pre-test to post-test.

Pre-scores in the Interest attitudes component was a statistically significant predictor of the gain-scores in that component ($t(49)$ = -2.44, p < 0.05). The coefficient of determination was low, r^2 = 0.11. That is, pre-scores in the Interest component explained about 11% of the variation in the gain-scores of that component. For a low pre-test score of 2, the conditional estimated mean gain was 0.40, with a 95% confidence interval of (-0.35, 1.15). Since the 95% confidence interval includes the value of zero in its range, it cannot be concluded that, on average, students' interest in statistics with a low pre-score of 2 improved from pre-test to post-test; Therefore, it is plausible to suggest that, for those students with a low pre-score of 2 in the Interest component, their interest in statistics did not change from pre-test to post-test.

For a high pretest score of 6 in the Interest component, the conditional estimated mean gain was -0.78, with a 95% confidence interval of (-1.23, -0.34). On average, students' interest in statistics for those with a high pretest score of 6 dropped from beginning to the end of their introductory statistics course.

Pre-scores in the Effort component were a statistically significant predictor of gain-scores in that attitudes component ($t(49) = -6.64$, $p < 0.05$). The coefficient of determination was moderate, $r^2 = 0.48$. That is, pre-scores in the Effort component explained about 48% of the variation in the gain-scores of that component. For a low pre-test score of 2, the conditional estimated mean gain was 3.19, with a 95% confidence interval of (2.05, 4.32). On average, students' indication of their planned effort to learn statistics with a low pre-score of 2 improved from pre-test to post-test; their indication of their planned effort to learn statistics at the end of their statistics course was more positive than what they reported at the beginning of their course.

For a high pretest score of 6 in the Effort component, the conditional estimated mean gain was -0.17, with a 95% confidence interval of (-0.44, 0.09). Since the 95% confidence interval includes the value of zero in its range, it cannot be concluded that, on average, students' indication of their planned effort to learn statistics for those with a high pretest score of 6 dropped from the beginning to the end of their introductory statistics course. Therefore, it is plausible to suggest that, for those students with a high pre-test score of 6 in the Effort component, their indication of their planned effort to learn statistics did not significantly change from pre-test to post-test.

4.11 Path Analysis

In this section, I describe the results of the path analysis that I used to answer the third research question of the study, regarding the interrelationships among social sciences students' attitudes towards statistics and their statistics outcomes. Path analysis is a procedure in structural equation modelling that enables researchers to evaluate specific hypothesized relationships among a set of variables in their study (Meyers et al., 2013). These hypothesized relationships are specified by paths drawn between the variables (Meyers et al., 2013).

Path analysis is an extension of multiple regressions, with many dependent variables that provide estimates of the regression coefficients and the significance of the hypothesized relationships among a set of variables (Meyers et al., 2013). In path analysis, some variables are defined as endogenous variables, which means having other variables in the hypothesized path model explain their variations (Meyers et al., 2013). Some variables are defined as exogenous variables, which means that they are not explained by other variables in the hypothesized path model, and are perhaps explained by some other variables beyond the scope of the model (Meyers et al., 2013).

For the current study, I adopted the same hypothesized path model as the one described by Emmioglu (2011) to evaluate the interrelationships among students' past mathematics achievement, their statistics outcomes (their statistics course grade and their willingness to use statistics in the remainder of their degree program and when employed) and their statistics attitudes by the end of their introductory statistics course. Like Emmioglu (2011), I used students' responses to post-version of SATS-36© for testing the structural model. I treated the attitudes components of Affect, Cognitive Competence, Value, Interest, and Effort as endogenous variables, and Difficulty and Mathematics Achievement as exogenous variables.

The component of Statistics Outcomes was hypothesized as the dependent variable, because it was expected that it would be predicted from other variables in the path model. Additionally, I examined the magnitude of the direct and indirect effects on the dependent variable (the component of Statistics Outcomes) and on the endogenous variables in the path model. Below is the same Figure 2 as the one presented earlier in Chapter 2, which illustrates the hypothesized path model in Emmioglu's (2011) approach to examining students' attitudes towards statistics by the end their course.

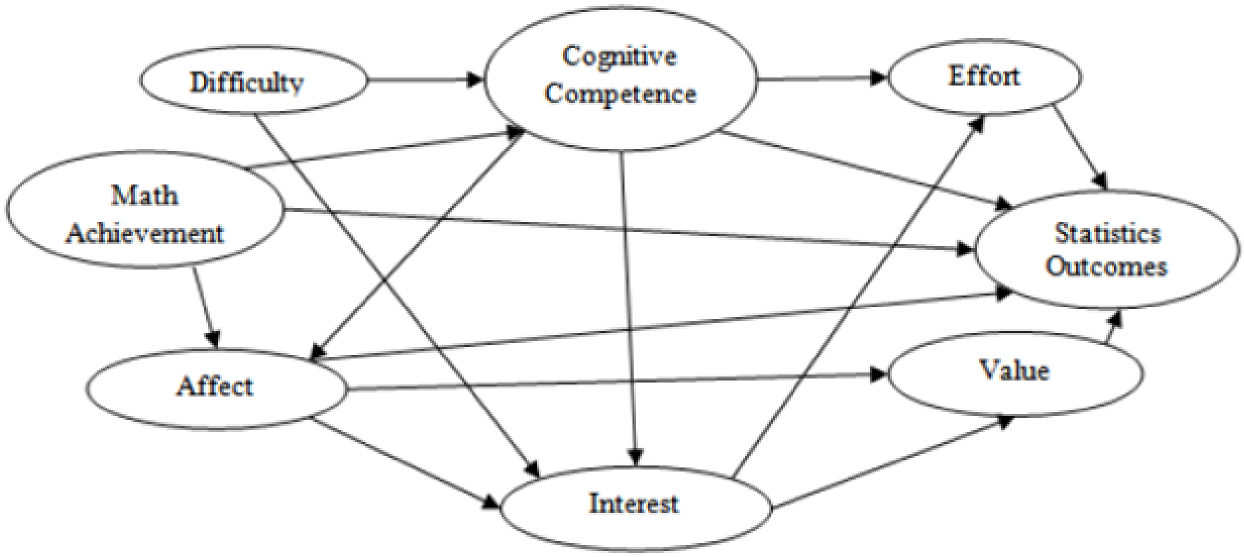

Figure 2. Conceptual Structure of the Statistics Attitudes-Outcomes Model (Emmioglu, 2011, p. 8)

Based on the theoretical path model, presented in Figure 2, there were 25 free parameters that needed to be estimated. These parameter estimates include: 16 path coefficients, 8 error variances, and 1 covariance between the two exogenous variables. Since there are eight variables in this model, the number of data points that could be estimated were: $\frac{8(8+1)}{2}$ = 36. When subtracting the number of free parameters to be estimated from the number of data points that could be estimated, the degrees of freedom, df was: 36 – 25 = 11. Since df = 11 > 0, the model was over-identified, which means that there were more values in the sample variance-covariance matrix, S (data points), than the population variance-covariance matrix, Σ (number of parameters to be estimated in the theoretical model). That means, if the path analysis suggested that the theoretical models need to be improved, new paths can be added to the model because there are 11 data points left to be estimated in the sample variance-covariance matrix, S.

In testing whether the theoretical model was supported by the sample data, the overall fit of the model was evaluated based on several fit indices (Meyers et al., 2013). Fit indices indicate how well the proposed interrelationships between the variables match the observed relationships

(Meyers et al., 2013). For the current study, the five most common fit measures described by Meyers, Gamst, and Guarino (2013) were used. These fit indices were the model's chi-square test-statistic (χ^2), the Goodness of Fit Index (GFI), the Root Means Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Normed Fit Index (NFI).

In order to establish a close fit between the data and hypothesized model, a nonsignificant chi-square statistic is preferred (Meyers et al., 2013). In terms of fit indices, GFI value has a similar connotation as the R^2 value (coefficient of determination) in the regression analysis (Kline, 2011), which refers to the proportion of variance in the sample correlation that is explained by the predicated model (Meyers et al., 2013). The GFI value of 0.90 or greater is indicative of an acceptable model (Meyers et al., 2013).

RMSEA value is the average residuals between the observed data and the expected model correlations (Meyers et al., 2013). RMSEA value of 0.08 or less is indicative of an acceptable model, whereas a value of greater than 0.10 is not (Meyers et al., 2013). The CFI and NFI values "are measures of fit relative to the independence model, which assumes that there are no relationships in the data (thus a poor fit) and the saturated model, which assumes a perfect fit" (Meyers et al., 2013, p.871). Values greater than 0.90 suggest an acceptable fit between the model and the data (Meyers et al., 2013).

For the current study, the value of the chi-square test statistic was statistically significant, χ^2= 29.3961, df = 11, p = 0.002, which indicated that the path model predicted relations that were significantly different from relations observed in the sample. Thus, the fit indices were examined. The GFI value, which was 0.881, did not indicate a reasonably adequate fit for the path model since the value was below the cut-off value of 0.90 (Meyers et al., 2013).

The CFI value, which was 0.915, met the criteria value and indicated an adequate fit between the data and the theoretical path model (Meyers et al., 2013). The NFI value, which was 0.880, did not indicate a reasonably adequate fit of the path model since the value was below the cut-off value of 0.90 (Meyers et al., 2013).

The RMSEA value, which was 0.181, was above criteria value of 0.10 to indicate a reasonably adequate fit (Meyers et al., 2013). The chi-square statistic and most of the fit indices indicated poor fit between the data and hypothesized model. Therefore, modification indices were assessed to improve the fit of the path model.

The modification indices suggested adding an error covariance between Effort and Difficulty components, which estimated decreasing the value for the chi-square test statistic by 9.211. Based on this suggestion, the original path model was modified and the chi-square statistic and fit indices were re-assessed. The value of the chi-square statistic was decreased from the original model to χ^2= 19.198, with df = 10. However, the chi-square statistic was still significant (p = 0.038), which indicated that the modified model still predicted relations that were significantly different from relations observed in the sample.

Therefore, the fit indices were examined. The values for GFI, CFI, and NFI were all above 0.90, which indicated an adequate fit between the data and the theoretical path model (Meyers et al., 2013). The RMSEA value was 0.134. Although the RMSEA value improved from the original model, it was still above the criteria value of 0.10 to indicate an adequate fit between the data and the theoretical path model. The chi-square statistic and the RMSEA value indicated poor fit between the data and the modified model.

Therefore, modification indices were assessed again, but in the modified model to improve the fit. The modification indices suggested adding an error covariance between

Cognitive Competence and Value attitude components, which estimated a decrease of the value of the chi-square statistic by 7.038. Based on this suggestion, the modified model was specified again and the chi-square statistic and fit indices were re-assessed. Table 4.10 illustrates the values of chi-square statistics and the fit indices for the original and the modified models to the original.

Table 4.10

Chi-square Statistics and Fit Indices for Path Models

Model	χ^2	df	GFI	RMSEA	CFI	NFI
Original	29.361*	11	0.881	0.181	0.915	0.880
Modification 1	19.198*	10	0.921	0.134	0.957	0.921
Modification 2	12.482	9	0.948	0.087	0.984	0.949

Note: χ^2 = Chi-square statistic; * $p < 0.05$; df = degrees of freedom; GFI = Goodness of Fit Index; RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; NFI = Normed Fit Index.

Based on the second modification to the original model, the value of the chi-square statistic was decreased to χ^2= 12.482, with df = 9 and p = 0.188, which was not statistically significant. The result of the chi-square test statistic indicated a close fit between the data and the hypothesized path model. Furthermore, the fit indices were assessed again. The GFI value, which was 0.948, indicated a good fit between the data and the theoretical model since it met the criteria value of being above 0.90 (Meyers et al., 2013). The RMSEA value, which was 0.087, indicated an adequate fit between the data and the theoretical model since its value was in the criteria range of 0.08 and 0.10 (Meyers et al., 2013).

The CFI value, which was 0.984, and the NFI value, which was 0.949, both indicated a good fit between the data and the theoretical model since they met the criteria of being above 0.90 (Meyers et al., 2013). Based on the evaluations of the chi-square test statistic and the values of fit indices, the improved model (second modification to the original model), indicated a reasonably adequate fit between the data and the theoretical path model. The improved model estimated the error covariances between Difficulty and Effort components, and between Cognitive Competence and Value components.

In addition to checking the improved model's fit indices, parameter estimates were examined for their statistically significant direct and indirect effects on the dependent variables. The parameter estimates are standardized path coefficients, which are analogous to beta weights (γ) in regression analysis (Meyers et al., 2013).

For the current study, the criteria described by Kline (2011) were used to indicate the magnitude of the effects of standardized path coefficients on the dependent variables. That is, standardized path coefficients close to 0.10 indicate small effects; values close to 0.30 indicate medium effects; and values of 0.50 and greater indicate large effects (Kline, 2011). Figure 3, on page 119, presents the standardized path coefficients of the improved model. The variables included in the path analysis are illustrated in rectangles instead of oval shapes because they are treated in the analysis as observed measurements.

The results from the improved model (second modification to the original model) revealed that there were medium, positive, statistically significant direct effects of past mathematics achievement (γ = 0.31, p < 0.05), Value component (γ = 0.36, p < 0.05) and Effort component (γ = 0.44, p < 0.05) on the Statistics Outcomes component. That is, when students had higher past mathematics achievement, viewed the subject of statistics as valuable (useful, relevant, and worthwhile) in their personal and professional lives, and spent a great deal of effort learning statistics, they had higher statistics outcomes at the end of their introductory statistics course.

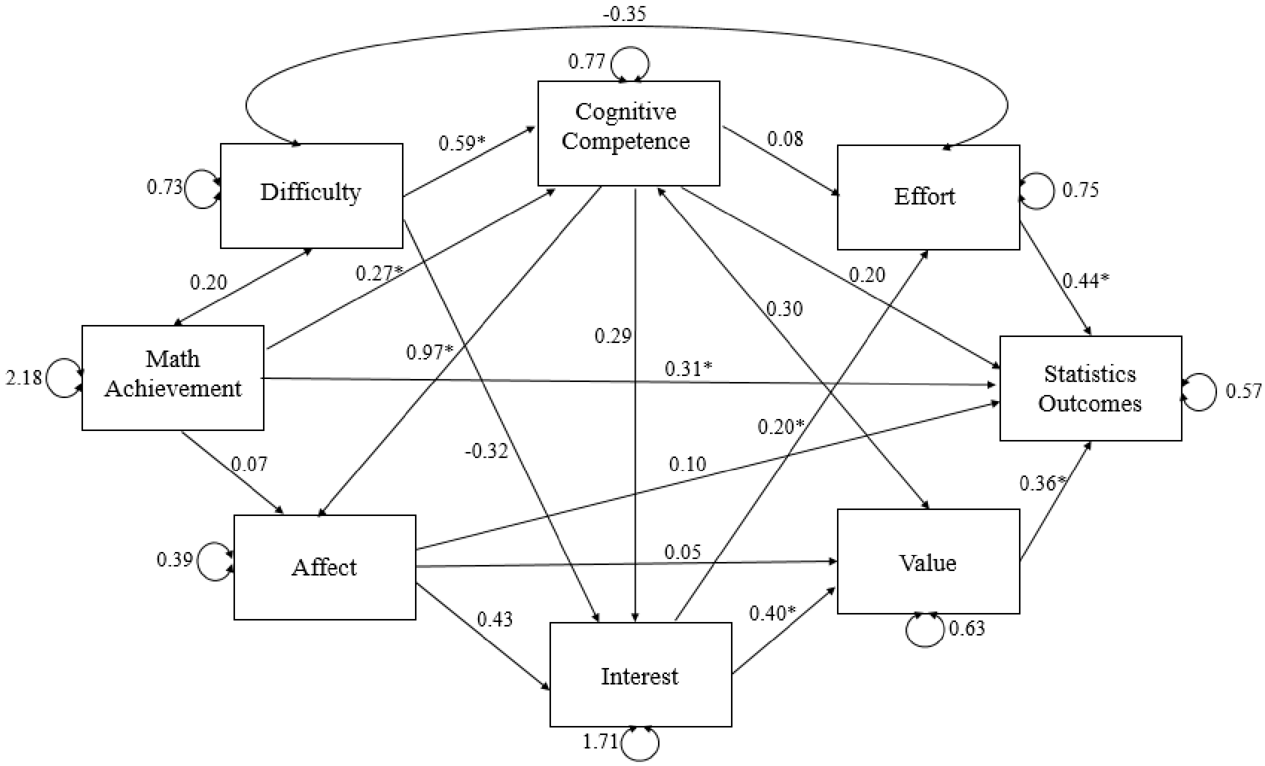

Figure 3. The Standardized Path Coefficients of the Improved Path Model.
Note: *p<0.05

The Affect and Cognitive Competence components did not have statistically significant direct effects on the Statistics Outcomes component. This means there was no evidence that students' feelings concerning statistics, and their perception of their capability in applying their skills and knowledge in doing statistics, contributed to their statistics outcomes at the end of their introductory statistics course.

The Interest component had positive, statistically significant direct effects on the Value and Effort components. The direct effect of Interest on Value was medium (γ = 0.40, p < 0.05). The direct effect of Interest on Effort was small (γ = 0.20, p < 0.05). These results indicated that students' interest in statistics predicted their perception of valuing the subject and effort to learn statistics, which, in turn, predicted their statistics outcomes at the end of their introductory statistics course. This means that students who had higher interest in statistics, valued the subject of statistics in their personal and professional lives, and spent a great deal of effort learning statistics had higher statistics outcomes at the end of their introductory statistics course.

The Cognitive Competence component had a very large, positive, statistically significant direct effect on the Affect component ($\gamma = 0.97$, $p < 0.05$). This means that when students had high self-regard for their capability in applying their skills and knowledge in doing statistics, they had more positive feelings toward statistics at the end of their introductory statistics course.

Past mathematics achievement and the Difficulty component had positive, statistically significant direct effects on the Cognitive Competence attitudes component. The direct effect of past mathematics achievement on Cognitive Competence was medium ($\gamma = 0.27$, $p < 0.05$), and the direct effect of Difficulty on Cognitive Competence was large ($\gamma = 0.59$, $p < 0.05$). These results indicate that students who reported doing well in their past mathematics courses and perceived statistics as an easy subject had a positive perception of their capabilities in doing statistics at the end of their introductory statistics course.

Taken together, these results demonstrated that students who reported doing well in their past mathematics courses and perceived statistics as an easy subject had higher cognitive competence in their capacity to apply their skills and knowledge in doing statistics, and therefore, had positive feelings toward statistics at the end of their introductory statistics course.

The Affect, Cognitive Competence, and Difficulty attitudes components did not have statistically significant direct effects on the Interest attitude component. This means there was no evidence that students’ feeling concerning statistics, their perception of their capability in applying their skills and knowledge in doing statistics, and their perception of the difficulty of the subject of statistics predicted their interest in statistics at the end of their introductory statistics course.

Additionally, the Affect attitudes component did not have a statistically significant direct effect on Statistics Outcomes and Value components. This means there was no evidence that students' feelings concerning statistics predicted their statistics outcomes and their perception of the value (usefulness, relevance, and worth) of the subject in their personal and professional lives at the end of their introductory statistics course. Past mathematics achievement did not have a statistically significant direct effect on the Affect attitudes component. There was no evidence that students' past mathematics achievement predicted their feelings concerning statistics at the end of their introductory statistics course.

The Cognitive Competence component did not have a statistically significant direct effect on the Statistics Outcomes and Effort components. This means there was no evidence that students' perception of their capability in applying their skills and knowledge in doing statistics predicted their statistics outcomes and their effort to learn statistics at the end of their introductory statistics course.

In addition to the standardized direct effects, standardized indirect, total indirect, and total effects were assessed. Standardized total indirect effects are the sum of standardized indirect effects via all of their presumed pathways in the model (Kline, 2011). Standardized total effect is the sum of standardized direct effect and total indirect effects via all of their presumed pathways in the model (Kline, 2011).

For the current study, the standardized direct, total indirect and total effects are presented in Table 4.11 on page 122. Next, I describe the total indirect effects of each of the six attitudes components and past mathematics achievement on the Statistics Outcomes component via their presumed pathways in the improved model.

Table 4.11

Standardized Direct, Total Indirect and Total Effects

		Affect	Cognitive Competence	Interest	Effort	Value	Statistics Outcomes
Past Math Achievement	Direct Effect	0.07	0.27*	-	-	-	0.31*
	Total Indirect	0.26*	-	0.22*	0.07	0.11	0.14*
	Total Effect	0.33*	0.27*	0.22*	0.07	0.11	0.45*
Difficulty	Direct Effect	-	0.59*	-0.32	-	-	-
	Total Indirect	0.57*	-	0.32	0.07	-0.07	0.10
	Total Effect	0.57*	0.59*	0.00	0.07	-0.07	0.10
Affect	Direct Effect	-	-	0.43	-	0.05	0.10
	Total Indirect	-	-	-	0.09	0.17	0.12
	Total Effect	-	-	0.43	0.09	0.22	0.22
Cognitive Competence	Direct Effect	0.97*	-	0.29	0.08	-	0.20
	Total Indirect	-	-	0.42	0.14*	0.33*	0.31
	Total Effect	0.97*	-	0.71*	0.22	0.33*	0.51*
Interest	Direct Effect	-	-	-	0.20*	0.40*	-
	Total Indirect	-	-	-	-	-	0.23*
	Total Effect	-	-	-	0.20*	0.40*	0.23*
Effort	Direct Effect	-	-	-	-	-	0.44*
	Total Indirect	-	-	-	-	-	-
	Total Effect	-	-	-	-	-	0.44*
Value	Direct Effect	-	-	-	-	-	0.36*
	Total Indirect	-	-	-	-	-	-
	Total Effect	-	-	-	-	-	0.36*

*$p<0.05$

Past mathematics achievement had a small, positive, statistically significant indirect effect on Statistics Outcomes ($\gamma = 0.14$, $p < 0.05$) through Cognitive Competence, Affect, Interest, Value, and Effort. This means those students who reported doing well in their previous mathematics courses, felt more competent in doing statistics, liked statistics more, were more interested in it, valued the subject more, and put more effort in learning statistics had higher statistics outcomes at the end of their course. Also, the Interest component had a medium, positive, statistically significant indirect effect on Statistics Outcomes ($\gamma = 0.23$, $p < 0.05$) through Value and Effort components. That is, students who were more interested in statistics and valued and spent more effort in learning statistics obtained higher statistics outcomes at the end of their introductory statistics course.

Although past mathematics achievement had no statistically significant direct effect on the Affect component, it had a medium, positive, statistically significant indirect effect on Affect ($\gamma = 0.26$, $p < 0.05$) through Cognitive Competence. This means that when students reported doing well in their past mathematics courses, their capability in applying their skills and knowledge in doing statistics were higher, and their feelings towards statistics were more positive at the end of their course. Past mathematics achievement also had a medium, positive, statistically significant indirect effect on Interest ($\gamma = 0.22$, $p < 0.05$) through Cognitive Competence and Affect. That is, those students who reported doing well in their past mathematics courses, felt more competent in doing statistics and liked statistics more, were more interested in statistics at the end of their course.

Although the Cognitive Competence component had no statistically significant direct effect on the Effort component, it had a small, positive, statistically significant indirect effect on Effort ($\gamma = 0.14$, $p < 0.05$) through Affect, and then Interest components. This means that, when students felt capable in applying their skills and knowledge in doing statistics, their feelings concerning statistics were more positive, which increased their interest in statistics and their effort to learn statistics at the end of their introductory statistics course.

The Cognitive Competence component also had a medium, positive, statistically significant indirect effect on the Interest component ($\gamma = 0.33$, $p < 0.05$) through the Affect component. That means students who felt more capable in applying their skills and knowledge in doing statistics had more positive feelings concerning statistics and were more interested in learning statistics. Lastly, the Difficulty component had a large, positive, statistically significant indirect effect on the Affect component ($\gamma = 0.57$, $p < 0.05$) through the Cognitive Competence component. That is, when students perceived the subject of statistics as less difficult, their competence in doing statistics was higher, and their feelings about statistics were more positive at the end of their introductory statistics course.

The main interest of the current study is comprised of the total standardized effects on the Statistics Outcomes component. The total standardized effects of past mathematics achievement, Cognitive Competence, Value, Interest, and Effort attitudes components on Statistics Outcomes were medium to large (Table 4.11). More specifically, past mathematics achievement, Cognitive Competence, Value, Interest, and Effort components had total standardized effects on Statistics Outcomes of: 0.45, 0.51, 0.36, 0.23, and 0.44 respectively.

However, the total standardized effects of the Affect and Difficulty components on the Statistics Outcomes component were small and not statistically significant (Table 4.11). These results revealed that, except for the Affect and Difficulty components, past mathematics achievement, Value, Interest, and Effort components contributed to predicting Statistics Outcomes through their presumed pathways.

Additionally, coefficient of determinations and R^2 values were examined to investigate the amount of variance accounted for by a set of variables and their presumed pathways in the hypothesized model. Table 4.12 presents these R^2 values.

Table 4.12

Squared Multiple Correlations R^2

Component	
Statistics Outcomes	0.66
Affect	0.77
Cognitive Competence	0.39
Value	0.49
Interest	0.25
Effort	0.09

The overall improved model explained 66% of variance in the Statistics Outcomes component. The overall improved model also explained 77% of variance in the Affect component, 39% of variance in the Cognitive Competence component, 49% of variance in the Value component, 26% of variance in the Interest component, and 9% of variance in the Effort component.

4.12 Summary of Results

The results of the current study revealed that on average, the participants had a somewhat neutral perception regarding their previous performance in mathematics. By the end of their introductory statistics course, students' feelings concerning statistics improved but remained somewhat negative. Their perception of their capability in applying their skills and knowledge in doing statistics improved and remained positive. Their view regarding the value of statistics in their personal and professional lives dropped but remained positive. Their perception of statistics as a less difficult subject improved but remained somewhat negative. Their interest in statistics dropped but remained positive.

They still reported spending a great deal of effort in learning statistics, but less effort than they had indicated at the beginning of their statistics course. Overall, the participants had neutral statistics outcomes, which included the measurements of their statistics achievement at the end of their course, and their willingness to use statistics in the future (after their statistics course).

The results of the present study showed that male and female students had similar attitudes toward statistics at both times of the test administration. Moreover, students in different years of study had similar attitudes toward statistics. There was a slight indication that first year students ($n = 5$) tended to like statistics more, felt more competent, valued the subject more, perceived statistics as less difficult, were more interested in statistics, and reported putting more effort into learning statistics at both times of the test administration.

This study investigated the changes in students' attitudes toward statistics at the beginning and the end of their statistics course. The participants' gain-scores (pre-scores subtracted from their post-scores) were conditioned on their pre-scores in each of the six attitudes components. Gain-scores had no association with participants' past mathematics achievement, their statistics achievement, and their statistics outcomes.

The results indicated that, except for students' effort to learn statistics, their pre-attitudes scores had weak relationships with their gain-scores. Although these associations, except in the Effort component, were weak, there were some noteworthy indications. The results showed that students who reported poor attitudes-scores regarding their feelings concerning statistics, their competency in applying their skills and knowledge in doing statistics, their valuing of the subject in their personal and professional lives, their perception of the difficulty of the subject of statistics, and their effort to learn statistics improved their attitudes by the end of their introductory statistics course. However, their interest in statistics remained unchanged, and, on average, they were still positive by the end of their introductory statistics course.

In regards to participants with high initial attitudes scores, students who reported liking statistics more, who perceived the subject as less difficult, and indicated putting more effort into learning statistics had attitudes scores that remained the same by the end of their course. However, those students who reported high competency in statistics, valued the subject more, and were more interest in statistics had attitudes scores that dropped by the end of their introductory statistics course.

The current study also investigated the interrelationships among students' past mathematics achievement, their statistics outcomes and their statistics attitudes by the end of their course. The structural model, which is named "Statistics Attitudes-Outcomes Model" proposed by Emmioglu (2011), was adopted to test these relationships. After making improvements to the hypothesized model, it was found that the improved model explained 66% of the variance in the Statistics Outcomes component. Participants' past mathematics achievement, their value of the subject, their interest in statistics, and their effort to learn statistics predicted their statistics outcomes through all their presumed pathways. This means that when students had high perceptions of their past mathematics achievement, valued the subject more, were more interested in statistics, and spent more effort in learning statistics, they had high statistics outcomes at the end of their statistics course.

Although, students' affect toward, their competency in, and their perception of the difficulty of statistics did not explain their statistics outcomes through all the presumed pathways, they did have important roles in the structural model. Students' cognitive competence in statistics predicted their affect toward statistics. That is, the more students felt competent in statistics, the more they liked the subject.

Students' past mathematics achievement predicted their cognitive competence in statistics. That is, the more students reported doing well in their past mathematics courses, the higher was their competency in statistics. Moreover, students' past mathematics achievement had an important role (indirectly) in explaining their statistics outcomes through their cognitive competence in statistics. This means that, the more students reported doing well in their past mathematics courses, the higher their competency in statistics was, and their feelings about statistics were more positive by the end of their course.

The results of the present study revealed that students' interest in statistics predicted the amount of time they invested in learning statistics and their valuing of the subject. That is, the more time they spent in learning statistics, and the more they valued the subject in their personal and professional lives, the more they became interested in statistics; in turn, they had higher statistics outcomes. Additionally, it was found that students' interest in and their affect toward statistics mediated the relationship between their cognitive competence in and their effort to learn statistics. That is, students who felt more competent in statistics and had more positive feelings concerning statistics became more interested in it, and, in turn, they put more effort into learning the subject by the end of their introductory statistics course.

Lastly, students' perception of the difficulty of the subject of statistics predicted their cognitive competence in doing statistics, and their feelings concerning statistics. That is, students who perceived the subject of statistics as less difficult had high competence in applying their skills and knowledge in doing statistics, and had positive feelings concerning statistics by the end of their introductory statistics course.

Chapter Five: Discussion

5.1 Introduction

In this chapter, I present the discussion and implications of the results of the current study. In the first part of this chapter, I revisit the research questions posed in Chapter One and discuss how the results of the current study compare with the existing literature. In the second part of this chapter, the implications of these results are presented to provide recommendations for future research and practice in statistics education.

5.2 The Research Questions

My thesis focuses on the research questions posed in Chapter One. Those questions were:

1. How do undergraduate social sciences students' attitudes toward statistics change from the beginning to the end of an introductory statistics course for the social sciences?
2. How do undergraduate social sciences students' past mathematics achievements, their statistics outcomes, their sex, and their year of study contribute to their attitudes toward statistics?
3. What are the structural interrelationships among undergraduate social sciences students' past mathematics achievements, their statistics attitudes at the end of the course, and their statistics outcomes?

5.3 Discussion of Each Research Question

5.3.1 Research Question 1: How do undergraduate social sciences students' attitudes toward statistics change from the beginning to the end of an introductory statistics course for the social sciences?

The results of the current study revealed that, on average, by the end of their introductory statistics course, students' feelings concerning statistics improved but remained somewhat negative. Their perception regarding their capability in applying their knowledge and skills in doing statistics improved and remained positive. Their perception regarding the value (usefulness, relevance, and worth) of statistics in their personal and professional lives dropped but remained positive.

Their perception of statistics as a less difficult subject improved but remained somewhat negative. Their interest in statistics dropped but remained positive. They still reported spending a great deal of effort to learn statistics, but less effort than what they had initially indicated at the beginning of their introductory statistics course.

The results described above were supported by earlier studies regarding students' feelings concerning statistics (Schau & Emmioglu, 2012), in terms of students' competency in applying their knowledge and skills in doing statistics (Chiesi & Primi, 2010), in terms of students' views of value (usefulness, relevance, and worth) of statistics in their personal and professional lives (Bond et al., 2012; Schau & Emmioglu, 2012), in terms of students' perception of the difficultly of statistics as a subject (Schau & Emmioglu, 2012), and in terms of students' interest in and their planned efforts to learn statistics (Bond et al., 2012; Schau & Emmioglu, 2012).

To investigate the changes in students' attitudes toward statistics, as in Millar and Schau (2010), the current study modeled students' gain-scores (pre-scores subtracted from post-scores) conditional on their pre-scores in each of the six attitudes components of: Affect, Cognitive Competence, Value, Difficulty, Interest, and Effort. The purpose of this modelling (regression to the mean) was to examine how the differences in pre-attitudes scores explain the differences in gain-attitudes scores in each of the six attitudes components.

The results of the current study revealed that pre-attitudes scores explained some of the variation in their corresponding gain-attitudes scores. The percentage of explained variation in the gain-scores was 8% in the Affect component, 14% in the Cognitive Competence component, 16% in the Value component, 8% in the Difficulty component, 11% in the Interest component, and, 48% in the Effort component. These results indicated that except in the Effort component, the differences in pre-attitudes scores weakly explained the differences in the gain-attitudes scores. That is, students' pre-attitudes scores had weak relationships with their gain-scores.

Although there were weak associations between pre-scores and gain-scores in all but the Effort attitudes component, there were some noteworthy indications of the regression analyses. Those students who reported pre-attitudes scores as low as 2 (on a 7-point Likert scale) in terms of Affect, Cognitive Competence, Value, Difficulty, and Effort had their attitudes scores improve by at least 0.50 points by the end of their introductory statistics course. However, in terms of Interest their attitudes remained unchanged. These results indicated that students who reported poor attitudes-scores regarding their feelings concerning statistics, their competency in applying their skills and knowledge in doing statistics, their valuing of the subject in their personal and professional lives, their perception of the difficulty of the subject of statistics, and their effort to learn statistics had improved their attitudes by the end of their introductory statistics course. The results of the current study regarding students' affect toward statistics, and their cognitive competence in doing statistics were consistent with Millar and Schau's (2010) results.

The current study revealed that students' interest in statistics remained unchanged; however, on average it was still positive by the end of their introductory statistics course. Additionally, although students' feelings concerning statistics improved by the end of their statistics course, on average, they reported that they still somewhat disliked statistics by the end of their course. This finding was consistent with an earlier study (Schau & Emmioglu, 2012).

Students who reported pre-attitudes scores as high as 6 (on a 7-point Likert scale) in terms of Affect, Difficulty, and Effort components had attitudes scores that remained unchanged by the end of their introductory statistics course. However, in regards to Cognitive Competence, Value, and Interest components, their attitudes scores dropped by at least 0.45 points by the end of their course. These results indicated that students who reported liking statistics more, who perceived the subject as less difficult, and indicated putting more effort into learning statistics, had attitudes scores that remained the same by the end of their course. However, students who reported high competency in applying their skills and knowledge in doing statistics, valued the subject more in their personal and professional lives, and were more interested in statistics had attitudes scores that dropped by the end of their introductory statistics course. Millar and Schau (2010) note that those students with high pre-attitudes scores are less likely to improve their scores since they have already reported high attitudes scores at the beginning of their introductory statistics course.

5.3.2 Research Question 2: How do undergraduate social sciences students' past mathematics achievements, their statistics course grade, their sex, and their year of study contribute to their attitudes toward statistics?

The current study found no statistically significant differences between male and female students' attitudes toward statistics at either time of test administration. These findings were consistent with previous studies (Cashin & Elmore, 2005; Hilton et al., 2004; Emmioglu, 2012). However, some studies have reported that female students had less positive attitudes toward statistics than male students (e.g., Mills, 2004; Roberts & Saxe, 1982; Schau, 2003b). Hilton, Schau and Olsen (2004) assert: “the inconsistent results could be due to variety of attitudes measure, students sample, and administration times used” (p. 95). Additionally, Ramirez, Schau, and Emmioglu (2012) argue: “male and female students may have taken different mathematics courses and achieved at different levels in these courses. Those courses may impact their statistics attitudes and together results in different statistics outcome by student gender” (p. 62).

The relationship between the participants’ years of study and their attitudes toward statistics were also examined at both times of the test administration. There were no statistically significant differences found between the participants’ years of study in any of the six attitudes components. These results were consistent with Emmioglu’s (2012) findings. In the current study, the descriptive statistical analyses revealed that, on average, first-year and second-year students tended to like statistics more, felt more competent in doing statistics, valued the subject more in their personal and professional lives, were more interested in statistics, and reported putting more effort into learning statistics than the third-year and fourth-year students. Although the reasons for differences in attitude were unclear, it might be that third- and fourth- year students tended to avoid taking their required statistics course because they were afraid of it. As pointed out in the existing literature, their fear of taking an introductory statistics course might be a result of their previous related-achievement or experiences in similar mathematics or statistics courses (e.g., Gal et al. 1997).

The results of Cashin and Elmore’s (2005) study showed that, as compared to younger students, older students perceived the subject of statistics as more difficult and felt less capable of applying their knowledge and skills in doing statistics. Researchers have pointed out that adults who have forgotten mathematics basics face academic and professional challenges (Gal, 2002; Murtonen, & Lehtinen, 2003; Reston, 2007; Steen, 2001). In the current study, there were more participants in the third or fourth year of their studies than in their first or second year. Moreover, most of the participants were domestic students who had obtained their high school diplomas in Ontario, which means that they only needed to complete up to grade 11 mathematics in order to be admitted into Humanities or Social Sciences programs at the participating university. Thus, for a majority of the participants, there had been a gap at least three years since taking a quantitative-based course. These gaps can make students anxious about learning statistics, and in turn affect their confidence in doing statistics (Koh & Khairi, 2014).

For the current study, participants' past mathematics achievement had no statistically significant correlations with changes in their attitudes toward statistics. The changes in attitudes were obtained by subtracting the pre-test scores from post-test scores. Therefore, relationships between participants' past mathematics achievement and each of the six attitudes components were examined separately at both times of the test administration. The results revealed that the participants' pre-scores, more than their post-scores in the Affect, Cognitive Competence, and Value attitudes components, had moderate to strong, statistically significant correlations with their past mathematics. These findings were supported by earlier studies (Carmona et al., 2005; Cashin & Elmore, 2005).

In terms of the Difficulty component, the participants' past mathematics achievement did not contribute to how they perceived the difficulty of the subject of statistics. Cashin and Elmore (2005) found that students who previously took more mathematics courses prior to their statistics course tended to perceive the subject of statistics as less difficult. In the current study, the majority of the participants did not have extensive former training in either mathematics or statistics, since their last mathematics course was in grade 11. This might explain the small relationship that was observed between participants' past mathematics achievement and their perception of the difficulty of the subject both at the beginning and at the end of their introductory statistics course.

In the current study, past mathematics achievements also had small, statistically significant correlations with students' interest in and effort to learn statistics both at the beginning and at the end of their introductory statistics course. These results were also consistent with a previous study conducted by Emmioglu (2011). As noted previously, the participants in the current study had little mathematical background. The majority of them completed high school in Ontario, and they had little basic knowledge of statistics (mostly at the grade 8 level). Therefore, they did not have sufficient opportunity to experience thinking statistically and to become interested in the subject. Moreover, their perception of their past mathematics achievement did not contribute to their interest in statistics by the end of their course.

For the current study, the participants' statistics achievement (their statistics course grade) had no statistically significant correlations with changes in their attitudes toward statistics. Correlations between the participants' attitudes toward statistics and their statistics achievement were examined separately at both times of the test administration. The results showed that post-attitudes scores had stronger associations with statistics achievement than the pre-attitudes scores. These findings were supported by earlier studies (e.g., Cashin & Elmore, 2005; Dempster & McCorry, 2009; Schau, 2003b).

There were no statistically significant associations between statistics achievement and the pre-scores in any of the six attitudes components. There were, however, statistically significant relationships between students' attitudes in terms of Affect and Cognitive Competence and their statistics achievement by the end of their introductory statistics course. This means that, at the end of their introductory statistics course, those students who had more positive feelings concerning statistics and felt more competent in applying their skills and knowledge in doing statistics had higher statistics achievement. These findings were consistent with previous studies (Cashin & Elmore, 2005; Dempster & McCorry, 2009; Emmioglu & Capa-Aydin, 2012; Schau, 2003b).

However, some findings in the current study were inconsistent with earlier studies (Cashin & Elmore, 2005; Dempster & McCorry, 2009). There was no statistically significant correlation between the participants' valuing of statistics in their personal and professional lives and their statistics achievement. Cashin and Elmore (2005) had 342 participating undergraduate and graduate students enrolled in an introductory statistics course, some of whom had taken several mathematics courses prior to taking their statistics course. Likewise, Dempster and McCorry (2008) had 82 psychology participants who had completed four statistics courses by the end of their second year. Their post-attitudes scores were collected at the end of their second year. It can be concluded that, unlike the current study, the participants in previously mentioned studies (Cashin & Elmore, 2005; Dempster & McCorry, 2009) had former experience in mathematics and/or statistics. Therefore, their valuing of the subject had a stronger contribution to their statistics achievement since the participants had more experience in mathematics or statistics courses and had more opportunities to practice their statistical skills.

Additionally, unlike the current study, in Cashin and Elmore's (2005) study, participants who viewed statistics as a less difficult subject had high statistics achievement. In the current study, there was no statistically significant association between students' perception of the difficulty of the subject of statistics and their statistics achievement. This finding was supported by earlier studies (Dempster & McCorry, 2009; Emmioglu, 2011).

As pointed out by Schau (2003b), students taking an introductory course in statistics should perceive the subject as neither easy nor difficult. This was the case for the participants in the present study. However, irrespective of whether the participants perceived statistics as an easy or difficult subject, their perception did not explain their statistics achievement. Moreover, on average, students in the present study did well in their statistics course regardless of how they perceived the difficulty of the subject of statistics.

In the current study, there was no statistically significant relationship between students' interest in statistics and their statistics achievement. This result was inconsistent with the findings from Emmioglu (2011). The result from the current study means that students' level of interest in statistics by the end of their course did not significantly contribute to their statistics achievement. Consistent with Emmioglu's (2011) findings, in the current study, there was a small to moderate, statistically significant relationship between students' indication of their planned effort to learn statistics and their statistics achievement. Those students who reported spending a great deal of effort to learn statistics by the end of their course had higher statistics achievement.

5.3.3. Research Questions 3: What are the structural interrelationships among undergraduate social sciences students' past mathematics achievements, their statistics attitudes at the end of the course, and their statistics outcomes?

The current study also investigated the interrelationships among students' past mathematics achievement, their statistics achievement and their statistics attitudes by the end of their course. To investigate these relationships, the structural model proposed by Emmioglu (2011), named "Statistics Attitudes-Outcomes Model", was adopted. After some modifications to improve the overall fit of data to the proposed model, it was found that the structural model explained 66% of the variance in statistics outcomes. This finding was consistent with Emmioglu's (2011) findings. In addition to the overall model fit, the contribution of each attitudes component for explaining the structural relationships was assessed.

The components of past mathematics achievement, Value, Interest and Effort had medium, positive, statistically significant total effects on the Statistics Outcomes component through all their presumed pathways. However, the components of Affect, Cognitive Competence, and Difficulty did not have statistically significant total effects on the Statistics Outcomes component via all their presumed pathways.

These results indicated that students' statistics outcomes, which were measured by their statistics course grade and their willingness to use statistics in the future (e.g., in the remainder of their degree program and when employed) were predicted by their past performance in their mathematics courses, their valuing of statistics in their personal and professional lives, their interest in statistics, and their reported effort to learn statistics. That is, when students had high perceptions of their past mathematics achievement, valued the subject more, were more interested in statistics, and spent more effort in learning statistics, they had high statistics outcomes at the end of their statistics course.

In regards to the total effects of past mathematics achievement, Cognitive Competence, Value, Interest, and Effort components on the Statistics Outcomes component, the results of the current study were in line with Emmioglu's (2011) findings. However, in terms of Affect, the results of the current study were inconsistent with Emmioglu's (2011) findings as she reported large, statistically significant total effects of Affect on Statistics Outcomes. Emmioglu (2011) collected data on post-attitudes scores from 247 undergraduates and graduate students in Turkey. On average, the participants in her study had positive views concerning statistics. In the current study, the participants were all undergraduate students who reported somewhat negative feelings concerning statistics at the end of their course.

Although in the current study the Affect component was not statistically significant in the tested model, it was statistically significant in explaining students' cognitive competence in statistics, their valuing of the subject, their perceived difficulty of the subject, and their interest in statistics. Moreover, consistent with Emmioglu's (2011) findings, the Difficulty component was not statistically significant in the tested model; however, it was statistically significant for explaining students' affect toward statistics, their cognitive competence in statistics, and their effort spent in learning statistics. As Emmioglu (2011) does, it can be concluded that each component in the model had important contributions for explaining statistics outcomes and for explaining the interrelationships among each of these.

The results of the current study revealed that the Effort component had a medium, statistically significant direct effect on Statistics Outcomes, which was supported by earlier findings (Emmioglu, 2011; Hood et al., 2012; Tempelaar et al., 2007). The direct effect of Effort component was positive, which indicated that the more students invested their time and effort in learning statistics, the higher their statistics outcomes were. This result supported the "Statistics Attitudes-Outcomes Model", and was consistent with Eccles and her colleagues' expected-value theory model (e.g., Eccles et al. 1983; Eccles & Wigfield, 2002) in which they proposed that relative cost (e.g., expanding a great deal of effort to learn statistics) directly relates to students' achievement-related choice and performance (e.g., statistics outcomes).

In the current study, the Value component had a medium, statistically significant direct effect on the Statistics Outcomes component. This finding was consistent with earlier studies (Emmioglu, 2011; Hood et al., 2012; Tempelaar et al., 2007). Like the direct effect of Effort, the direction of the effect of Value was positive, which indicated that the more students valued the subject of statistics in their personal and professional lives, the higher their statistics outcomes were. This result supported the “Statistics Attitudes-Outcomes Model” and was consistent with Eccles and her colleagues’ expected-value theory model (e.g., Eccles et al. 1983; Eccles & Wigfield, 2002) in which they proposed that subjective task value (e.g., valuing statistics) relates to students’ achievement-related choices and their performance (e.g., statistics outcomes).

However, Sorge and Schau (2002) indicated that the direct effect of the Value component on statistics achievement was not statistically significant. Their findings were inconsistent with the expected-value theory of achievement and motivation in mathematics education (e.g., Eccles et al. 1983). As pointed out by Emmioglu (2011), these studies should be considered cautiously by virtue of students’ diverse cultural and educational background. Sorge and Schau (2002) collected data on 264 undergraduate engineering students in the U.S.A. Tempelaar et al. (2007) collected data on a large number (n = 1618) of undergraduate business and economics students in the Netherlands. Hood et al. (2012) collected data on 149 undergraduate psychology students in Australia. Emmioglu (2011) collected data on 247 undergraduate and graduate students in Turkey in diverse programs of study (education, psychology, sociology, economics, business administration, applied mathematics, and engineering). It can be inferred that, in all three of these studies (Emmioglu, 2011; Sorge & Schau, 2002; Tempelaar et al., 2007), participating students had diverse cultural and educational backgrounds. Therefore, their conceptions of the value (usefulness, relevance, and worth) of the subject of statistics in their personal and professional lives were perceived somewhat differently. As in the current study, Emmioglu (2011) included students from the social sciences programs. Therefore, it is appropriate to compare the current study’s findings with Emmioglu’s (2011) results in terms of the relationship between students' valuing of the subject of statistics in their academic and professional lives, and their statistics outcomes (e.g., their willingness to use statistics in their future employment).

Lastly, in the current study, participants' past mathematics achievement had a medium and statistically significant direct effect on statistics outcomes, a result that is supported by earlier findings (Emmioglu, 2011; Hood et al., 2012; Sorge and Schau, 2002). The direct effect of past mathematics achievement was positive. That is, when students had a positive perception of their past performance in mathematics, their statistics outcomes were high. This result is reflected in the "Statistics Attitudes-Outcomes Model".

In the present study, the direct effect of past mathematics achievement on the Affect component was not statistically significant, which is contrary to the proposed "Statistics Attitudes-Outcomes Model". This means that students' perception of their previous achievements in mathematics did not contribute to their feelings concerning statistics by the end of their statistics course. Emmioglu (2011) argues that students' previous achievement-related experiences in mathematics might differ from their previous achievement-related experiences in statistics. She adds that students do not necessarily need to report high achievements in their previous mathematics courses in order to report liking statistics. Her viewpoint is supported by the argument made by prominent researchers in statistics education who posit: "students who may not be strong in mathematics may work hard and enjoy statistics" (Garfield & Ben-Zvi, 2007, p. 379-380). As noted earlier, the participants in the present study did not have strong mathematical backgrounds and, on average, they reported doing somewhat poorly in their previous mathematics courses and somewhat disliked statistics by the end of their course.

In contrast to the prior posited lack of direct effect of past mathematics achievement on students' affect toward statistics, the current study revealed that students' past mathematics achievement had a positive, statistically significant direct effect on their cognitive competence in doing statistics. This result was supported by an earlier study (Hood et al., 2012), which indicated that the more students reported doing well in their past mathematics courses, the higher their competency in statistics was. This finding supported the “Statistics Attitudes-Outcomes Model”, and was consistent with Eccles and her colleagues’ expected-value theory model (e.g., Eccles et al. 1983; Eccles & Wigfield, 2002), in which they proposed that an individual’s previous achievement-related experiences and affective memories relate to their self-conception regarding their abilities.

Additionally, this finding supported the theory of self-efficacy in mathematics education. Bandura (1977) describes self-efficacy as “people’s judgement of their capabilities to organize and execute courses of action required to attain designed types of performance” (p. 391). Warwick (2008) asserts that successful achievement in previous mathematical assessments will likely strengthen self-efficacy, whereas repeated failures in mathematics will likely weaken belief in self-efficacy.

Moreover, the current study revealed that students’ past mathematics achievement had a small, statistically significant indirect effect on their affect through their cognitive competence in statistics. This means that the more students reported doing well in their past mathematics courses, the higher their competency in doing statistics was, and, in turn, the more likely they were to have positive feelings about statistics by the end of their course. This finding supported the “Statistics Attitudes-Outcomes Model”.

The result of the current study showed that the Interest component had a medium, statistically significant direct effect on the Effort and Value components. These findings were supported by earlier studies (Emmioglu, 2011; Tempelaar et al. 2007). The direction of the effect was positive, which indicated that the more students were interested in statistics, the more they invested their time and effort in learning statistics, and the more they valued the subject of statistics in their personal and professional lives. These findings supported the "Statistics Attitudes-Outcomes Model" in terms of the interrelationships among the three distinct attitudes components of Interest, Effort, and Value.

However, these attitudes components were posited as one component in terms of subjective task value in the expected-value theory model (Eccles & Wigfield, 2002). Eccles and her colleague proposed that students' expectancy of success has a reciprocal relationship with their subject task value, which encompasses four domains. These include: interest-enjoyment value, which refers to the immediate enjoyment one experiences by engaging in the task, attainment value, which refers to the importance one gives to completing a task, utility value, which refers to how one views the usefulness of doing a task for a personal future goal, and relative cost, which refers to how one assesses the amount time a task requires for completion and loss of engagement in other activities as a consequence of doing that task.

Although in the current study there was no statistically significant direct effect of students' cognitive competence on their effort to learn statistics, their affect toward and their interest in statistics mediated the relationship. This means that students who felt more competent in applying their skills and knowledge to doing statistics and liked the subject more became more interested in statistics, and, in turn, put more effort into learning the subject. This finding was in line with Emmioglu's (2011) result and supported the "Statistics Attitudes-Outcomes Model", the expected-value theory model (Eccles & Wigfield, 2002), and self-determination theory applied to education (Ryan & Deci, 2000).

Self-determination theory posits that individuals' growth, social development, and well-being are facilitated by their need for competence, autonomy, and relatedness (Ryan & Deci, 2000). This means that "people must not only experience competence or efficacy, they must also experience their behavior as self-determined for intrinsic motivation to be evidence" (Ryan & Deci, 2000, p. 70). Intrinsic motivation is fostered by having "choice, awareness of feelings, and opportunities for self-direction…because they allow people a greater feeling of autonomy" (Ryan & Deci, 2000, p. 70).

Application of self-determination theory in the field of education means understanding that students' intrinsic motivation (interest) in their subject is enhanced by their belief in their own competency, sense of ownership, and feelings of relatedness (Ryan & Deci, 2000). In addition, the expected-theory model proposes that students' self-conception of their abilities and their affective reactions and memories contribute to their interest-enjoyment value, which in turn influence their achievement-related choices and performance (e.g., Eccles & Wigfield, 2002).

The results of the current study also showed that the Cognitive Competence component had a large, positive, statistically significant direct effect on the Affect component. This finding was supported by earlier findings (Emmioglu, 2011; Tempelaar et al., 2007; Sorge & Schau, 2002), which indicated that the higher students' competency in applying their skills and knowledge in statistics, the more they reported having positive feelings concerning statistics. This finding supported the "Statistics Attitudes-Outcomes Model".

As in Emmioglu's (2011) finding, the component of Cognitive Competence had no direct effect on the Effort and statistics outcomes components. That is, the extent to which students felt competent in applying their skills and knowledge in doing statistics did not contribute to their statistics outcomes and their effort to learn statistics.

Since the Interest component is in between the Cognitive Competence and Effort components, it is possible that Interest reduced the direct effect of Cognitive Competence on Effort and statistics outcomes. Despite not having a direct effect, Cognitive Competence had an important role (indirectly) for explaining the components of Effort and statistics outcomes. Therefore, these findings supported the self-efficacy theory (Bandura, 1977), the expected-value theory (Eccles & Wigfield, 2002), and self-determination theory (Ryan & Deci, 2000). These theories posit that students with positive judgements of their capabilities will perform better than those who do not (e.g., Eccles & Wigfield, 2002; Ryan & Deci, 2000).

The Cognitive Competence component had, however, a medium, positive, statistically significant indirect effect on Value through Affect and Interest components. This finding supported the "Statistics Attitudes-Outcomes Model" and was consistent with earlier findings (Arumugam, 2014; Emmioglu, 2011; Dauphinee et al., 1997; Tempelaar et al., 2007). That is, when students' competency in statistics was higher, their feelings concerning statistics and their interest in the subject were also higher, and their conception of the value (usefulness, relevance, and worth) of statistics for their academic and professional lives was higher. This result also supported the expected-value theory model, which proposes that students' self-conception of their abilities relates to their affective reactions and memories, and through that relates to their interest-enjoyment and attainment value of the task (Eccles & Wigfield, 2002)

In the current study, the Affect component had no statistically significant direct effect on statistics outcomes. This result was consistent with Emmioglu's (2011) findings, but inconsistent with Sorge and Schau's (2002) findings. Additionally, the Affect component did not have a statistically significant indirect effect on Value through Interest. This finding was inconsistent with earlier studies (Emmioglu, 2011; Sorge & Schau, 2002). Together, these findings were contrary to the "Statistics Attitudes-Outcomes Model".

The current study and Emmioglu's (2011) study used students' statistics outcomes as the dependent variable, which was based on students' statistics course grade, and their willingness to use statistics in the remainder of their degree program and when employed. However, Sorge and Schau (2002) used students' statistics achievement as their dependent variable in their structural model, which was measured only in terms of students' statistics course assessment. Moreover, their participants were undergraduate engineering students.

However, in the current study, the participants were undergraduate social sciences students. Likewise, Emmioglu's (2011) study included students from the social sciences. As described earlier in this thesis, social sciences students tend to have negative related-achievement experiences with mathematics, and have little exposure to mathematics based on the type and the number of courses completed during their high school years; or, they have forgotten the basics (Carmona et al. 2005; Lalayants, 2012; Malik, 2015; Murtonen, & Lehtinen, 2003). These factors can create challenges for social sciences students when learning basic statistics.

In the structural model, the components of Interest and Value are in between Affect and statistics outcomes. The Interest component had a statistically significant indirect effect on statistics outcomes. The Value component had a statistically significant direct effect on statistics outcomes. Therefore, based on the present study's findings, it can be concluded that, despite not having a direct effect, students' affect toward statistics was an important factor for explaining their statistics outcomes. Moreover, these findings supported the expected-value theory model, which posited that students' affective memories relates to their subjective task value and their expectation of success, as well as their achievement-related choices and their performance (Eccles & Wigfield, 2002).

In the current study, the Difficulty component had a large, positive, statistically significant direct effect on the Cognitive Competence component. This finding was consistent with earlier studies (Emmioglu, 2011; Sorge & Schau, 2002), and supported the "Statistics Attitudes-Outcomes Model". That is, the more students perceived the subject of statistics as less difficult, the higher their competency in statistics was.

Additionally, the Difficulty component had a large, positive, statistically significant indirect effect on Affect through the Cognitive Competence component. This result was consistent with Emmioglu's (2011) findings and supported the "Statistics Attitudes-Outcomes Model". That is, when students' perception of the difficulty of the subject of statistics was less, their competency in doing statistics was higher, and in turn, their feelings concerning statistics were more positive. This finding also supported the expected-value theory model, which proposes that students' perception of the difficulty of a task relates to their self-conception of abilities and their affective reactions and memories (Eccles & Wigfield, 2002).

The Difficulty component did not have a statistically significant direct or indirect effect on the Interest component. This finding was inconsistent with Emmioglu's (2011) result. However, as Difficulty is situated in between Cognitive Competence and Interest components in the structural model, it had an important role in the structural model.

In the current study, the Cognitive Competence component had a large, positive, statistically significant total effect on Interest through all its presumed pathways. These pathways included the direct effect of Cognitive Competence on Interest, and the indirect effect of Cognitive Competence on Interest through Affect. The results indicated that students' interest in statistics was greater when their competence in statistics increased. Additionally, the increase in their competency was positively related to their feelings concerning statistics. Therefore, these findings supported the expected-value theory model, which proposes that students' perception of the difficulty of a task relates to their self-conception of abilities, their interest, and their expectation of success (Eccles & Wigfield, 2002).

Additionally, the current study revealed that the attitudes-scores in the Difficulty and Effort components had error variances that were negatively covaried. That is, students' perception of the difficulty of the subject and their effort to learn statistics had a negative reciprocal relationship. This means that students who perceived the subject of statistics as less difficult put less effort into learning statistics. Students who put less effort into learning statistics perceived the subject of statistics as less difficult.

Moreover, the current study revealed that attitudes-scores in the Cognitive Competence and Value components had error variances that were positively covaried. That is, students' competence in doing statistics and their valuing of the subject had a positive reciprocal relationship. This means that students who felt more competent in applying their skills and knowledge in doing statistics valued the subject of statistics more in their academic and professional lives. Students who valued the subject of statistics more felt more competent in doing statistics. Therefore, in the current study, the two mentioned reciprocal associations were added to the "Statistics Attitudes-Outcomes Model". As a result, the hypothesized path model was improved. The data—students' attitudes-scores—adequately fit the improved model.

5.4 Future Research

The results of the current study can be generalized to its target population, which consists of all undergraduate social sciences students enrolled in an introductory statistics course for the social sciences. The current study assessed students' attitudes toward statistics twice in their statistics course, once at the beginning and another time at the end of their course, in order to examine the changes in their attitudes. The instrument SATS-36© (e.g., Schau, 2003b) was used to assess students' attitudes toward statistics.

Moreover, the current study investigated the interrelationships among undergraduate social sciences students' past mathematics achievement, their statistics outcomes, and their statistics attitudes by the end of their course. To investigate these interrelationships, the current study used and made improvements to the hypothesized structural model, which is named "Statistics Attitudes-Outcomes Model", proposed by Emmioglu (2011) and based on the expected-value theory model of achievement and motivation in mathematics education (e.g., Eccles & Wigfield, 2002). Thus, it is suggested that future studies use these frameworks and extend them in other domains such as different student populations.

Based on the review of the literature on student's attitudes toward statistics, it was apparent that there were not enough studies that explored affective domains and their relationship with students' statistics outcomes. However, this study revealed that students' attitudes were related to their statistics outcomes, which was consistent with previous findings (e.g., Cashin & Elmore, 2005; Emmioglu, 2011; Sorge & Schau, 2002). By examining the existing literature, it was also realized that a majority of studies on students' attitudes toward statistics were conducted in the United States and European countries. There seems to be a lack of extensive research on attitudes toward statistics that represents Canadian students.

It is suggested that future studies examine changes in students' attitudes toward statistics, and the interrelationships among their past mathematics achievement, their statistics attitudes and their statistics outcomes in different Canadian provinces so that the findings can be generalized to different student populations in Canada. Researchers can then conduct cross-comparisons of students' attitudes about statistics based on Canadian studies.

The current study found that students' past mathematics achievement predicted their statistics outcomes. Additionally, it predicted their competence in statistics. These findings were in line with self-efficacy theory (Bandura, 1977) and the expected-value theory (Eccles & Wigfield, 2002). These theorists posited that students' interpretations of their past performance and related-achievement relates to their affective memories, and self-conceptions of their capabilities in similar domains. Therefore, the current study investigated students' past mathematics achievement and their perceptions of their past performance in mathematics. The findings revealed that, on average, students perceived their past performance in mathematics as neither poor nor good. It was also found that about 20% of the participants did not take a grade 11 mathematics course, and a majority of students were in the upper years of their program of studies. Therefore, there had been a gap of a few years since their last mathematics course. These gaps can impose challenges for teaching and learning statistics (e.g., Reston, 2007).

The current study could not investigate the relationship between students' past mathematics achievement (e.g., at the high school level) and their self-reports of their past performance in mathematics, because there was a lack of information regarding the participants' past mathematics achievement at the high school level. Moreover, the type of mathematics courses that students completed in high school differed among them. Therefore, it is suggested that future studies assess the level of students' mathematical knowledge in terms of the topics they need to know prior to taking an introductory statistics course (e.g., Peck et al., n.d.). This way, educators can identify the initial level of students' competencies in mathematics, and consequently design and deliver introductory statistics courses appropriately (Chiesi & Primi, 2010; Dempster & McCorry, 2009; Emmioglu, 2011).

Most of the participants in the present study obtained their high school diploma in Ontario. According to the Ontario Mathematics Curriculum for Grades 11 and 12, students are expected to complete three mathematics courses in order to graduate from high school. This means that they do not need to take a grade 12 mathematics course. Moreover, students who plan to enrol in humanities or social sciences programs at the participating university are not required to complete a senior-level high school mathematics course. Therefore, they are less likely to take the grade 12 mathematics of data management, which is currently the only course in the Ontario Mathematics Curriculum at the secondary level that can develop students' statistical literacy, reasoning, and thinking. With the exception of the bivariate association between two quantitative variables, all other important basic statistical ideas such as the nature of variability in data, the notion of sampling distribution, probabilistic thinking, and statistical inference (NCTM, 2000) are omitted statistical topics in the Ontario Mathematics Curriculum for grades 9 to 11. Thus, it is suggested that future research examines the effects of including statistical ideas into Ontario's grades 9 to 11 mathematics courses on developing students' statistical literacy, reasoning and thinking. In addition, future studies might investigate the effect of integrating statistical concepts into Ontario's grades 9 to 11 mathematics courses on students' attitudes toward statistics.

Beck and Kosnik (2014) indicate that passion for a subject can model the love of learning for students, and therefore motivate students to engage, participate, and keep learning that subject. Thus, it is important to conduct studies on how pre-service and in-service elementary and secondary school mathematics teachers in Ontario and across Canada perceive teaching statistics, distinguish the subject of statistics from mathematics, and how they model the value, (usefulness, relevance, and worth) of the subject of statistics for students. Moreover, it is suggested that future studies examine pre-service and in-service teachers' self-efficacy in teaching statistics, and their attitudes toward statistics in Ontario and across Canada. Future studies might also investigate the relationship between students' and teachers' attitudes toward statistics in Ontario and in other provinces in Canada.

Motivated by statistics educators (Gal, 2002; Parke, 2008; Rumsey, 2002), an aspect of the course under study required students to work with their peers on a project in order to develop their statistical literacy. This project aimed at providing students with opportunities to read and reflect on an article of their choice from the field of social sciences that included a statistical methods section for conducting research. Students welcomed the idea of creating images (e.g., posters, paintings, pamphlets, videos, 3-D models, puzzles, and Prezi presentations) in order to demonstrate the ways in which they had internalized and understood the statistical information presented in their chosen article, and how those statistical messages continued to affect their everyday lives. It is thus recommended that future research employ qualitative studies by interviewing students about their experiences, with inclusion of a project in their statistics course. In this regard, future studies can shed light on how students take ownership of their statistical learning and find the subject of statistics interesting, worthwhile, relevant, and useful for their future career goals.

5.5 Implications for the Practice of Statistics Education

The purpose of the present study was to investigate the changes in social sciences students' attitudes toward statistics and the interrelationships among their past mathematics achievement, their statistics attitudes and their statistics outcomes in a discipline-specific approach to teaching statistics for the social sciences. Furthermore, the current study examined the relationships between students' attitudes toward statistics and their sex, their year of study, their past mathematics achievement, and their statistics course grade.

In the current study, by the end of their introductory statistics course, students' feelings concerning statistics and their perception of the difficulty of the subject improved but remained somewhat negative. Their cognitive competence in doing statistics improved and remained positive. Their valuing of the subject, their interest in, and their effort to learn statistics dropped but remained positive. These results have several implications for future teaching of an introductory statistics course for undergraduate social sciences students.

In order to keep undergraduate social sciences students interested in learning statistics, an introductory statistics course should provide students with ample opportunities to realize the value (usefulness, relevance, and worth) of learning statistics for their field of study. In doing so, students will be more likely to enjoy and put in the effort needed to learn statistics. Moreover, they will be more likely to use statistics after they leave their statistics course (e.g., in the remainder of their degree program and in their future employment).

The course under study had two hours of lecture each week for twelve weeks. In addition, there was a one-hour tutorial session each week for eleven weeks. The tutorials reviewed concepts from the previous week's lecture contents for about 30 minutes, and in the last 20 minutes, a quiz was given to students. Thus, it can be argued that there was not enough time allocated to make statistics relevant for the social sciences students either in the lectures or in the tutorials. Students did not receive enough opportunities to practice, discuss, and communicate statistical ideas with their peers, their teaching assistant, and their course instructor in the lectures and in the tutorials. Therefore, it is suggested that departments that offer introductory statistics courses consider increasing the weekly lecture-sessions to three hours.

Instructors of introductory statistics courses for the social sciences should consider removing quizzes from the tutorials so that students have more time to discuss and communicate statistical ideas with their peers, which is essential in their field of study. Moreover, students will have more time to discuss challenging questions in their tutorials. In that regard, their competency in statistics will be increased, and in turn, their feelings toward, their interest in, and their valuing of the subject of statistics will be more positive.

It is also suggested that instructors of an introductory statistics course for the social sciences use online platforms to quiz students on statistical topics on a weekly basis. This way, students will be encouraged to review statistical ideas outside of the classroom. Instructors should provide students with a reasonable amount of time to complete the weekly online quizzes. This is an especially important consideration for students who have accessibility needs, or have test anxiety. Furthermore, the quiz questions should use worthwhile and relevant statistical problems from the field of social sciences so that students find them meaningful and interesting to work on. The quiz questions should be neither hard nor easy; rather they should build students' confidence in doing statistics. Additionally, the quiz questions should prepare students for the midterm test and the final exam in their statistics course. Therefore, students will be more likely to invest their time in doing the weekly quizzes, as they realize that the completion of quiz questions will result in successful statistics course outcomes.

The current study found no significant differences in attitudes toward statistics between male and female students at either time of test administration. However, the descriptive statistical analyses revealed differences in attitudes toward statistics among students in different years of study. Compared to the first-year and the second-year students, the third-year and the fourth-year students had somewhat negative feelings concerning statistics, felt less competent in doing statistics, valued the subject less in their academic and professional lives, perceived the subject as more difficult, were less interested in, and put less effort into learning statistics. Furthermore, their statistics outcomes were somewhat below the average score. Although it is unclear why these differences in attitudes exist between students in lower and upper years of their studies, some inferences can be made.

Undergraduate social sciences students who avoid taking their introductory statistics course until the upper years of their studies will most likely enter their statistics course with anxious feelings toward the subject. They may also view the course only as a requirement for their degree program, and as a result, their interest in the subject may be less than that of other students in the course. This can affect their feelings concerning statistics and their valuing of the subject in their field. It is suggested that undergraduate social sciences programs make changes to their degree requirements and advise students to take their introductory statistics course before entering the third year of their program of study. Also, instructors of statistics should collaborate with faculties from the social sciences in order to integrate quantitative literacy across the undergraduate curriculum in the social sciences programs. Undergraduate social sciences students need to realize the usefulness of the subject of statistics not only in their introductory statistics course, but in almost all of their social sciences courses.

In terms of changes in students' attitudes, the current study provided some noteworthy indications for future teaching of an introductory statistics course for the social sciences. Students who had somewhat negative feelings concerning statistics felt less competent in doing statistics, valued the subject less, perceived the subject as more difficult, and reported putting less effort into learning statistics, improved their attitudes by the end of the course. However, students who reported high competency in statistics, valued the subject more, and were more interested in statistics, had less positive attitudes in these domains by the end of the course. These findings might be attributed to the ways in which students perceived the difficulty of the statistics course under study.

The statistics course under study here is designed for social sciences students with little mathematical background. Therefore, the statistical contents were presented at a slower pace as compared to another introductory statistics course that is offered in the same department at the participating university. It can be inferred that those social sciences students who had stronger mathematical backgrounds were not challenged enough in the course under study. They might have found the course easy. Therefore, their attitudes toward statistics by end of the course either remained the same as what they initially reported or dropped.

The findings from the current study's examination of interrelationships among undergraduate social sciences students' past mathematics achievement, their attitudes toward statistics, and their statistics outcomes have several implications for future teaching of an introductory statistics course for social sciences students. The current study indicated that students' past mathematics achievement, their valuing of, their interest in, and their effort to learn statistics predicted their statistics outcomes by the end of their statistics course. Additionally, their past mathematics achievement predicted their competence in doing statistics, and, in turn, their affect toward statistics.

Together, these results indicated that students' perception of their past achievement in mathematics was an important predictor of their attitudes toward statistics and their statistics outcomes by the end of their introductory statistics course. This means that students who reported doing well in their previous mathematics courses had high competence in doing statistics, positive feelings toward statistics, and high statistics outcomes. It is thus suggested that departments who offer introductory statistics courses assess students' attitudes toward statistics and their mathematical knowledge, based on the topics that they need to know for succeeding in an introductory statistics course, at the start of the course. This way, they can better shape the structure of their introductory courses and the ways in which they need to be delivered to students. For instance, based on the results of assessing students' mathematical knowledge prior to taking an introductory statistics course, instructors can recommend to their students that they review the mathematical topics that constitute adequate preparation for the course.

Departments that offer introductory statistics courses should design a preparatory course that reviews mathematical topics such as working with numbers, operations, and algebraic expressions in order to build students' competency in doing statistics prior to taking an introductory statistics course. These mathematical topics should use data from the field of social sciences in order to demonstrate the worth, relevance, and usability of learning statistics for the social sciences students. Thus, students can develop positive feelings toward statistics, become interested in learning the subject, and put in the effort needed to learn statistics.

Lastly, it is suggested that instructors make short videos or adopt premade ones on what they discuss in their lectures on a weekly basis, and embed in them quiz questions for students to answer. These videos can support students who need to review statistical concepts multiple times. They can also provide students with immediate opportunities to self-assess their statistical knowledge and understanding. Thus, students can become competent in applying their skills and knowledge in doing statistics, become interested in learning the subject, realize the value (usefulness, relevance, and worth) of learning statistics in their personal and professional lives, and, in turn have high statistics outcomes.

References

Agresti, A., & Finlay, B. (2009) *Statistical Methods for the Social Sciences* (4^{th} ed.). Upper Saddle River, NJ: Pearson Prentice Hall, Inc.

Arumugan, R. N. (2014). Student's Attitude Towards Introductory Statistics Course At Public Universities Using Partial Least Square Analysis. Interdisciplinary Journal of Contemporary Research in Business, *6*(4), 94-124.

Atkinson, J. W. (1957). Motivational Determinants of risk-taking behavior. *Psychological Review, 64*, 359-372.

Bandura, A. (1977). Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review, 84*(2), 191-215.

Beck, C. (2010). Moral/Values Education: Teachers Modelling a Way of Life and Helping Students Develop Their Way of Life. Lecture at Kobe Shinwa Women's University.

Beck, C. & Kosnik, C. (2014). *Growing as a Teacher: Goals and Pathways of Ongoing Teacher Learning.* The Netherlands: Sense Publishers.

Beck, C. & Kosnik, C. (2006). The starting point: Constructivist accounts of learning. In K. Leithwood, P. McAdie, N. Basica, & A. Rodrigue (Eds.), *Teaching for Deep Understanding: What Every Educator Needs to Know* (pp. 17-25). Thousand Oaks, CA: Corwin Press.

Ben-Zvi, D., & Garfield, J. B. (Eds.). (2004). *The challenge of developing statistical literacy, reasoning and thinking*. Dordrecht, The Netherlands: Kluwer Academic Publishers.

Bond, M. E., Perkins, S. N., & Ramirez, C. (2012). Students' Perceptions of Statistics: An Exploration of Attitudes, Conceptualizations, and Content Knowledge of Statistics. *Statistics Education Research Journal, 11*(2), 6-25.

Carnell, L. J. (2008). The Effect of a Student-Designed Data Collection Project on Attitudes Toward Statistics. *Journal of Statistics Education*, *16*(1). Retrieved from http://www.amstat.org/publications/jse/v16n1/carnell.html

Carmona, J., Martinez, R. J., & Sanchez, M. (2005). Mathematical background and attitudes toward statistics in a sample of Spanish college students. *Psychological Reports*, *97*(1), 53–62.

Cashin, S.E. & Elmore, P.B. (2005). The survey of attitudes toward statistics scale: A construct validity study. *Educational and Psychological Measurement*, *65*, 509-524.

Chance, B. (2002). Components of Statistical Thinking and Implications for Instruction and Assessment. *Journal of Statistics Education, 10*(3). Retrieved from http://www.amstat.org/publications/jse/v10n3/chance.html

Cerrito, P. B. (1999). Teaching Statistical Literacy. *College Teaching*, *47*(1), 9–13.

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

Cobb, P. (1994). Where Is the Mind? Constructivist and Sociocultural Perspectives on Mathematical Development. *Educational Researcher*, *23*(7), 13-20.

Creswell, J. W. (2012). *Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research*. Boston, MA: Pearson Education, Inc.

Cronbach, L. J. (1984). *Essentials of Psychological Testing*. Fourth Edition. New York: Harper and Row.

Dauphinee, T. L., Schau, C., & Stevens, J. J. (1997). Survey of Attitudes Toward Statistics: Factor structure and factorial invariance for females and males. *Structural Equation Modeling*, *4*, 129-141.

Davis, A. & Mirick, R. G. (2015). MSW Students' Perceptions of Relevance and Application of Statistics: Implications for Field Education. *Journal of Teaching in Social Work*, *35*, 317-336.

delMas, R. (2002). Statistical literacy, reasoning, and learning: A commentary. *Journal of Statistics Education, 10*(3). Retrieved from http://www.amstat.org/publications/jse/v10n3/delmas_discussion.html

delMas, R. (2004). A comparison of mathematical and statistical reasoning. In D. Ben-Zvi & J. Garfield (Eds.), *The challenge of developing statistical literacy, reasoning and thinking* (pp. 79-95). Dordrecht, The Netherlands: Kluwer Academic Publishers.

Dempster, M., & McCorry, N. K. (2009). The role of previous experience and attitudes toward statistics in statistics assessment outcomes among undergraduate psychology students. *Journal of Statistics Education, 17*(2). Retrieved from http://www.amstat.org/publications/jse/v17n2/dempster.html

Dewey, J. (1910). *How we think*. Boston: D. C. Heath.

Dewey, J. (1938). *Experience and education*. New York: Collier MacMillan.

Eccles, J. S., & Wigfield, A. (2002). Motivational Beliefs, Values and Goals. *Annual Review of Psychology*, *53*, 109-132.

Eccles, J., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J. L. & Midgley, C. (1983). Expectancies, values, and academic behaviors in *Achievement and Achievement Motives: Psychological and Sociological Approaches, ed. J. T. Spence* (pp. 75-146). San Francisco, W.H. Freeman and Company.

Emmioglu, E. (2011). A structural equation model examining the relationships among mathematics achievement, attitudes toward statistics, and statistics outcomes (Unpublished doctoral dissertation). Middle East Technical University, Ankara, Turkey.

Emmioglu, E., & Capa-Aydin, Y. (2012). Attitudes and Achievement in Statistics: A Meta-Analysis Study. *Statistics Education Research Journal, 11*(2), 95-102.

Ernest, P. (1991). *The philosophy of mathematics education*. New York: Falmer Press.

Franklin, C. A., Kader, G., Mewborn, D., Moreno, J., Peck, R., Perry, M., & Scheaffer, R. (2005). Guidelines for assessment and instruction in statistics education: A pre-K-12 curriculum framework (GAISE Report). Retrieved from www.amstat.org/education/gaise/

Field, A. (2009). *Discovering Statistics Using SPSS.* Thousand Oaks, CA: Sage

GAISE College Report ASA Revision Committee (2016). *Guidelines for Assessment and Instruction in Statistics Education College Report*. Retrieved from http://www.amstat.org/education/gaise.

Gal., I. (2002). Adults' statistical literacy: meanings, components, responsibilities. *International Statistical Review, 70*, 1-26.

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

Gal, I., Ginsburg, L., & Schau, C. (1997). Monitoring attitudes and beliefs in statistics education. In I. Gal & J.B. Garfield (Eds.), *The Assessment Challenge in Statistics Education* (pp. 37-51). Amsterdam, Holland: IOS Press.

Garfield, J. (2002). The Challenge of Developing Statistical Reasoning. *Journal of Statistics Education, 10*(3). Retrieved from ww2.amstat.org/publications/jse/v10n3/garfield.html

Garfield, J. & Ahlgren, A. (1988). Difficulties in learning basic concepts in probability and statistics: Implication for research. *Journal for Research in Mathematics Education, 19*(1), 44-63.

Garfield, J., & Ben-Zvi, D. (2005). A framework for teaching and assessing reasoning about variability. *Statistics Education Research Journal, 4*(1), 92-99.

Garfield, J., & Ben-Zvi, D. (2007). How students learn statistics revisited: A current review of research on teaching and learning statistics. *International Statistical Review, 75*(3), 372-396.

Garfield, J., & Ben-Zvi, D. (2008). Developing students' statistical reasoning: Connecting research and teaching practice: Springer.

Gattuso, L. (2006). Statistics and Mathematics. Is it possible to create fruitful links? In A. Rossman & B. Chance (Eds.), *Proceedings of the Seventh International Conference on Teaching Statistics*. Salvador, Bahia, Brazil. Retrieved from http://iase-web.org/documents/papers/icots7/1C2_GATT.pdf

Hacker, A. (2016). *The Math Myth: and other STEM delusions*. New York: The New Press.

Hampden-Thompson, G., & Sundaram, V. (2013). Developing Quantitative Research Skills and Conceptualising an Integrated Approach to Teaching Research Methods to Education Students. *The All Ireland Journal of Teaching and Learning in Higher Education, 5*(3), 901-9024.

Hilton, S. C., Schau, C., & Olsen, J. A. (2004). Survey of Attitudes Toward Statistics: Factor Structure Invariance by Gender and by Administration Time. *Structural Equation Modelling, 11*(1), 92-109.

Hood, M., Creed, P. A., & Neumann, D. L. (2012). Using The Expectancy Value Model of Motivation to Understand The Relationship Between Student Attitudes and Achievement in Statistics. *Statistics Education Research Journal, 11*(2), 72-85.

Horn, I. S. (2012). Strength *in Numbers: Collaborative Learning in Secondary Mathematics.* Reston, VA: The National Council of Teachers of Mathematics.

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling* (3rd Ed.). New York, NY: Guilford Press.

Koh, D., & Khairi Zawi, M. (2014). Statistics Anxiety among Postgraduate Students. *International Education Studies, 7*(13), 166-174.

Korkmaz S, Goksuluk D, & Zararsiz G (2014). MVN: An R Package for Assessing Multivariate Normality. *The R Journal. 6*(2), 151-162.

Kutner, M. H., Nachtsheim, C., Neter, J., & Li, W. (2005). *Applied Linear Statistical Models* (5th Ed.). New York, NY: McGraw-Hill Irwin.

Lalayants, M. (2012). Overcoming Graduate Students' Negative Perceptions of Statistics. *Journal of Teaching in Social Work*, 32, 356–375.

Levin, J., James A.F., & Forde, D. R. (2014). *Elementary Statistics in Social Research 12th Edition.* Upper Saddle River, NJ: Pearson.

Linnenbrink, E. A., & Pintrich, P. R. (2003). The role of self-efficacy beliefs in student engagement and learning in the classroom. *Reading & Writing Quarterly*, *19*, 119-137.

Makar, K., & Rubin, A. (2009). A framework for thinking about informal statistical inference. *Statistics Education Research Journal, 8*(1), 82-105.

Malik, S. M. (2015). Undergraduates' Statistics Anxiety: A Phenomenological Study. *The Qualitative Report*, *20*(2), 120-133.

Meyers, L., Gamst, G., & Guarino, A. J. (2013). *Applied Multivariate Research Design and Interpretation*. Thousand Oks, CA: Sage Publication, Inc.

Millar, A. M., & Schau, C. (2010). Assessing Students' Attitudes: The Good, the Bad, and the Ugly. *Proceedings of the Joint Statistical Meetings,* 1133-1143.

Mills, J. D. (2004). Students' attitudes toward statistics: Implications for the future. *College Student Journal, 38*(3), 349–361.

Moore, D. S. (1997). New Pedagogy and New Content: The Case of Statistics. *International Statistical Review, 65*(2), 123-165.

Moore, D. S. (1998). Statistics among the liberal arts. *Journal of the American Statistical Association*, *93*(444), 1253-1259.

Murtonen, M. (2005). Learning of Quantitative Research Methods. University of Turku. Turku, Finland. Retrieved from http://iase-web.org/documents/dissertations/05.Murtone.Dissertation.pdf

Murtonen, M., & Lehtinen, E. (2003). Difficulties Experienced by Education and Sociology Students in Quantitative Methods Courses. *Studies in Higher Education, 28*(2), 171-185.

Murtonen, M., & Titterton, N. (2004). Earlier mathematics achievement and success in university studies. *Nordic Studies in Mathematics Education*, *4*, 3-14.

Murtonen, M., Olkinuora, E., Tynjälä, P., & Lehtinen, E. (2008). Do I need research skills in working life? University students' motivation and difficulties in quantitative methods courses. *Higher Education, 56*(5), 599-612.

National Council of Teachers of Mathematics (1989). *Curriculum and evaluation standards for school mathematics*. Reston, VA: National Council of Teachers of Mathematics.

National Council of Teachers of Mathematics (2000). *Principles and Standards for School Mathematics.* Reston, VA: National Council of Teachers of Mathematics.

Olson, J. M., & Zanna, M. P. (1993). Attitude and Attitudes Change. *Annual Review of Psychology, 44*(1), 154-194.

Ontario Schools Kindergarten to Grade 12 (2016). *Policy And Program Requirement.* Retrieved from http://www.edu.gov.on.ca/eng/document/policy/os/onschools_2016e.pdf

Onwuegbuzie, A. J., & Wilson, V. A. (2003). Statistics anxiety: Nature, etiology, antecedents, effects, and treatments – a comprehensive review of the literature. *Teaching in Higher Education, 8*(2), 195-209.

Peck, R., Gould, R., & Utts, J. (n.d.). Mathematics Prerequisite for Success in Introductory Statistics. Retrieved From http://www.utdanacenter.org/wp-content/uploads/math_prerequisites_for_success_in_intro_statistics.pdf

Parke, C. S. (2008). Reasoning and Communicating in the Language of Statistics. *Journal of Statistics Education, 16*(1). Retrieved from http://www.amstat.org/publications/jse/v16n1/parke.html

Ramirez-Faghih, C. A. (2012). Fostering Change in College Students' Statistical Reasoning and Motivation Through Statistical Investigation. Doctoral Dissertation. University of California Davis. Davis, CA. Retrieved from http://iase-web.org/documents/dissertations/12.Ramirez.Dissertation.pdf

Ramirez, C., Schau, C., & Emmioglu, E. (2012). The importance of attitudes in statistics education. *Statistics Education Research Journal, 11*(2), 57-71.

Reston, E. (2007). Model of Student Learning in Graduate Statistics Education: Towards Statistical Literacy and Research Competence. International Statistical Institute, 56th Session. Retrieved from http://iase-web.org/documents/papers/isi56/CPM81_Reston.pdf

Roberts, D. M., & Bilderback, E.W. (1980). Reliability and validity of a statistics attitude survey. *Educational and Psychological Measurements, 40*, 235-238.

Roberts, D. M., & Saxe, J. E. (1982). Validity of a statistics attitude survey: A follow up study. *Educational and Psychological Measurements, 42*, 907-912.

Rumsey, D. J. (2002). Statistical Literacy as a Goal for Introductory Statistics Courses. *Journal of Statistics Education, 10*(3). Retrieved from http://www.amstat.org/publications/jse/v10n3/rumsey2.html

Ryan, R. M., & Deci E. L. (2000). Self determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68-78.

Schau, C. (2003a). *Survey of Attitudes Toward Statistics (SATS-36©)*. Retrieved from http://evaluationandstatistics.com/

Schau, C. (2003b). *Students' attitudes: The "other" important outcome in statistics education*. Paper presented at the Joint Statistical Meetings, San Francisco, CA. Retrieved from http://evaluationandstatistics.com/

Schau, C., & Emmioglu (2011). Do introductory statistics courses in the United States improve students' attitudes? *Statistics Education Research Journal, 11*(2), 86-94.

Schau, C., Stevens, J., Dauphinee, T. L., & Del Vecchio, A. (1995). The development and validation of the Survey of Attitudes Toward Statistics. *Educational and Psychological Measurement, 55*, 868-875.

Sears, A. & Cairns, J. (2010). *A Good Book In Theory: Making Sense Through Inquiry* (2nd Ed.) Toronto: University of Toronto Press.

Shaughnessy, M.J. (1992). Research in probability and statistics: Reflections and directions. In D.A. Grouws (Ed.), *Handbook of Research on Mathematics Teaching and Learning* (pp. 465-494). New York, NY: Macmillan.

Shaughnessy, J. M. (2007). Research on statistics learning and reasoning. In F. K. Lester (Ed.), *The second handbook of research on mathematics* (pp. 957-1010). Information Age Pub Inc.

Shaughnessy, J. M., Garfield, J., & Geer, B. (1996). Data handling. In A. J. Bishop, K. Clements, C. Keitel, J. Kilpatrick & C. Laborde (Eds.), *International handbook of mathematics education* (vol. 1, pp. 205-237). Dordrecht, Netherlands: Kluwer.

Slootmaeckers, K., Kerremans, B., & Adriaensen, J. (2014). Too Afraid to Learn: Attitudes towards Statistics as a Barrier to Learning Statistics and to Acquiring Quantitative Skills. *Politics, 34*(2), 191-200.

Sorge, C., & Schau, C. (2002, April). *Impact of engineering students' attitudes on achievement in statistics: A structural model.* Paper presented at the Annual Meeting of the American Educational Research Association, New Orleans, Louisiana.

Sovak, M. M. (2010). The Effect of Student-driven Projects on the Development of Statistical Reasoning. Doctoral Dissertation. University of Pittsburgh. Pittsburgh, PA retrieved from http://iase-web.org/documents/dissertations/10.Sovak.Dissertation.pdf

Steen, L. A. (2000). Mathematics, Numeracy, and Statistics. *Proceedings of the 2000 AMESA National Congress.* Association of Mathematics Educators of South Africa, pp. 367-372.

Steen, L.A. (2001). The case for quantitative literacy. In L. A. Steen (Ed), *Mathematics and democracy: The case for quantitative literacy.* Princeton, NJ: The National Council on Education and the Disciplines.

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

The Ontario Curriculum Grades 9 and 10 Mathematics (2005). Retrieved From http://www.edu.gov.on.ca/eng/curriculum/secondary/math910curr.pdf

Thompson, P. W. (2013). Constructivism in mathematics education. In S. Lerman (Ed.), *Encyclopedia of mathematics education [online]*. Berlin: Springer. doi: 10.1007/SpringerReference_313210 2013-05-10 00:00:07 UTC.

Utts, J. (2003). What Educated Citizens Should Know about Statistics and Probability. *The American Statistician, 57*(2), 74-79.

Vahey, P., Rafanan, K., Patton, C., Swan, K., Hoot, M., Kratcoski, A., & Stanford, T. (2012). A cross-disciplinary approach to teaching data literacy and proportionality. *Educational Studies in Mathematics, 81*(2).

Verhoeven, P. S. (2009). Quality in statistics education determinants of student outcomes in methods & statistics education at universities and colleges. Unpublished doctoral dissertation, Utrecht University, Amsterdam, The Netherlands.

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.

Warwick, J. (2008). Mathematical self-efficacy and student engagement in the mathematics classroom. *MSOR Connections*, *8*(3), 31-37.

Watson, J. (1997). Assessing Statistical Thinking Using the Media. *The Assessment Challenge in Statistics Education*, eds. I. Gal and J. Garfield, Amsterdam: IOS Press and International Statistical Institute.

Watson, J. M. (2006). Statistical literacy- A global goal. In A.H. Schoenfeld (Ed.), *Statistical Literacy at School: Growths and Goals* (pp. 247-272). Mahwah, New Jersey: Lawrence Erlbaum Associates.

Watson, J., & Callingham, R. (2003). Statistical Literacy: A complex hierarchal construct. *Statistics Education Research Journal, 2*(2), 3-46.

Wild, C. J., & Pfannkuch, M. (1999). Statistical thinking in empirical enquiry (with discussion). *International Statistical Review*, *67*(3), 223-265.

Wise (1985). The development and validation of a scale measuring attitudes toward statistics. *Educational and Psychological Measurement, 45*, 401-405.

Zeidner, M. (1991). Statistics and mathematics anxiety in social science students: some interesting parallels. *British Journal of Educational Psychology, 61*, 319-328.

Appendix A

Survey of Attitudes Toward Statistics

Pre

DIRECTIONS: The statements below are designed to identify your attitudes about statistics. Each item has 7 possible responses. The responses range from 1 (strongly disagree) through 4 (neither disagree nor agree) to 7 (strongly agree). If you have no opinion, choose response 4. Please read each statement. Mark the one response that most clearly represents your degree of agreement or disagreement with that statement. Try not to think too deeply about each response. Record your answer and move quickly to the next item. Please respond to all of the statements.

SATS Pre-questionnaire Section 1

	Strongly disagree			Neither disagree nor agree			Strongly Agree
I plan to complete all of my statistics assignments	1	2	3	4	5	6	7
I plan to work hard in my statistics course.	1	2	3	4	5	6	7
I will like statistics.	1	2	3	4	5	6	7
I will feel insecure when I have to do statistics problems.	1	2	3	4	5	6	7
I will have trouble understanding statistics because of how I think.	1	2	3	4	5	6	7
Statistics formulas are easy to understand.	1	2	3	4	5	6	7
Statistics is worthless.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pre-questionnaire Section 2

	Strongly disagree			Neither disagree nor agree			Strongly Agree
Statistics is a complicated subject.	1	2	3	4	5	6	7
Statistics should be a required part of my professional training.	1	2	3	4	5	6	7
Statistical skills will make me more employable.	1	2	3	4	5	6	7
I will have no idea of what's going on in this statistics course.	1	2	3	4	5	6	7
I am interested in being able to communicate statistical information to others.	1	2	3	4	5	6	7
Statistics is not useful to the typical professional	1	2	3	4	5	6	7
I plan to study hard for every statistics test.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pre-questionnaire Section 3

	Strongly disagree			Neither disagree nor agree			Strongly Agree
I will get frustrated going over statistics tests in class.	1	2	3	4	5	6	7
Statistical thinking is not applicable in my life outside my job.	1	2	3	4	5	6	7
I use statistics in my everyday life.	1	2	3	4	5	6	7
I will be under stress during statistics class.	1	2	3	4	5	6	7
I will enjoy taking statistics courses.	1	2	3	4	5	6	7
I am interested in using statistics.	1	2	3	4	5	6	7
Statistics conclusions are rarely presented in everyday life.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pre-questionnaire Section 4

	Strongly disagree			Neither disagree nor agree			Strongly Agree
Statistics is a subject quickly learned by most people.	1	2	3	4	5	6	7
I am interested in understanding statistical information.	1	2	3	4	5	6	7
Learning statistics requires a great deal of discipline.	1	2	3	4	5	6	7
I will have no application for statistics in my profession.	1	2	3	4	5	6	7
I will make a lot of math errors in statistics.	1	2	3	4	5	6	7
I plan to attend every statistics class session.	1	2	3	4	5	6	7
I am scared by statistics.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pre-questionnaire Section 5

	Strongly disagree			Neither disagree nor agree			Strongly Agree
I am interested in learning statistics.	1	2	3	4	5	6	7
Statistics involves massive computations.	1	2	3	4	5	6	7
I can learn statistics.	1	2	3	4	5	6	7
I will understand statistics equations.	1	2	3	4	5	6	7
Statistics is irrelevant in my life.	1	2	3	4	5	6	7
Statistics is highly technical.	1	2	3	4	5	6	7
I will find it difficult to understand statistical concepts.	1	2	3	4	5	6	7
Most people have to learn a new way of thinking to do statistics.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pre-questionnaire Additional Questions - 1

Please notice that the labels for each scale on the rest of this page change from item to item.

How well did you do in mathematics courses you have taken in the past?	Very poorly 1	2	3	4	5	6	Very well 7
How good at mathematics are you?	Very poor 1	2	3	4	5	6	Very good 7
In the field in which you hope to be employed when you finish school, how much will you use statistics?	Not at all 1	2	3	4	5	6	Great deal 7
How confident are you that you can master introductory statistics material?	Not at all confident 1	2	3	4	5	6	Very confident 7
Are you required to take this statistics course (or one like it) to complete your degree program?	Yes 1			No 2			Don't know 3
If the choice had been yours, how likely is it that you would have chosen to take any course in statistics?	Not at all likely 1	2	3	4	5	6	Very likely 7

Please check that you have answered every question in this section (unless you intentionally left the question blank).

SATS Pre-questionnaire Additional Questions - 2

What grade do you expect to receive in this course?

1. A +	5. B	9. C -	13. F
2. A	6. B-	10. D+	
3. A-	7. C+	11. D	
4. B+	8. C	12. D-	

In order to describe the characteristics of your class as a whole, we need your responses to the following items. Please circle your response, or specify.

Your sex: 1. Male 2. Female

Your age: Under 19 19-20 21-22 23-30 over 30

Where you completed high school:

In Ontario

Elsewhere in Canada. Please specify_______________________________

Outside Canada. Please specify___________________________________

When you completed high school:

Last year (2015) 2009-2014 before 2009

Please check that you have answered every question on this page (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

THANKS FOR YOUR HELP!

Appendix B

Survey of Attitudes Toward Statistics

Post

DIRECTIONS: The statements below are designed to identify your attitudes about statistics. Each item has 7 possible responses. The responses range from 1 (strongly disagree) through 4 (neither disagree nor agree) to 7 (strongly agree). If you have no opinion, choose response 4. Please read each statement. Mark the one response that most clearly represents your degree of agreement or disagreement with that statement. Try not to think too deeply about each response. Record your answer and move quickly to the next item. Please respond to all of the statements.

SATS Post-questionnaire Section 1

	Strongly disagree			Neither disagree nor agree			Strongly Agree
I tried to complete all of my statistics assignments.	1	2	3	4	5	6	7
I worked hard in my statistics course.	1	2	3	4	5	6	7
I like statistics.	1	2	3	4	5	6	7
I feel insecure when I have to do statistics problems.	1	2	3	4	5	6	7
I have trouble understanding statistics because of how I think.	1	2	3	4	5	6	7
Statistics formulas are easy to understand.	1	2	3	4	5	6	7
Statistics is worthless.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Post-questionnaire Section 2

	Strongly disagree			Neither disagree nor agree			Strongly Agree
Statistics is a complicated subject.	1	2	3	4	5	6	7
Statistics should be a required part of my professional training.	1	2	3	4	5	6	7
Statistical skills will make me more employable.	1	2	3	4	5	6	7
I have no idea of what's going on in this statistics course.	1	2	3	4	5	6	7
I am interested in being able to communicate statistical information to others.	1	2	3	4	5	6	7
Statistics is not useful to the typical professional.	1	2	3	4	5	6	7
I tried to study hard for every statistics test.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Post-questionnaire Section 3

	Strongly disagree						Strongly Agree
I get frustrated going over statistics tests in class.	1	2	3	4	5	6	7
Statistical thinking is not applicable in my life outside my job.	1	2	3	4	5	6	7
I use statistics in my everyday life.	1	2	3	4	5	6	7
I am under stress during statistics class.	1	2	3	4	5	6	7
I enjoy taking statistics courses.	1	2	3	4	5	6	7
I am interested in using statistics.	1	2	3	4	5	6	7
Statistics conclusions are rarely presented in everyday life.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose “Neither disagree nor agree.”

SATS Post-questionnaire Section 4

	Strongly disagree			Neither disagree nor agree			Strongly Agree
Statistics is a subject quickly learned by most people.	1	2	3	4	5	6	7
I am interested in understanding statistical information.	1	2	3	4	5	6	7
Learning statistics requires a great deal of discipline.	1	2	3	4	5	6	7
I will have no application for statistics in my profession.	1	2	3	4	5	6	7
I make a lot of math errors in statistics.	1	2	3	4	5	6	7
I tried to attend every statistics class session.	1	2	3	4	5	6	7
I am scared by statistics.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose “Neither disagree nor agree.”

SATS Post-questionnaire Section 5

	Strongly disagree			Neither disagree nor agree			Strongly Agree
I am interested in learning statistics.	1	2	3	4	5	6	7
Statistics involves massive computations.	1	2	3	4	5	6	7
I can learn statistics.	1	2	3	4	5	6	7
I understand statistics equations.	1	2	3	4	5	6	7
Statistics is irrelevant in my life.	1	2	3	4	5	6	7
Statistics is highly technical.	1	2	3	4	5	6	7
I find it difficult to understand statistical concepts.	1	2	3	4	5	6	7
Most people have to learn a new way of thinking to do statistics.	1	2	3	4	5	6	7

Please check that you have answered every question in this section (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Post-questionnaire Additional Questions – 1

NOTICE that the labels for the scale on each of the following items differ from those used above.

How good at mathematics are you?	Very poor 1	2	3	4	5	6	Very good 7
In the field in which you hope to be employed when you finish school, how much will you use statistics?	Not at all 1	2	3	4	5	6	Great deal 7
How confident are you that you have mastered introductory statistics material?	Not at all confident 1	2	3	4	5	6	Very confide 7
As you complete the remainder of your degree program, how much will you use statistics?	Not at all 1	2	3	4	5	6	Great deal 7
If you could, how likely is it that you would choose to take another course in statistics?	Not at all likely 1	2	3	4	5	6	Very likely 7
How difficult for you is the material currently being covered in this course?	Very easy 1	2	3	4	5	6	Very difficu 7

Please check that you have answered every question in this section (unless you intentionally left the question blank).

SATS Post-questionnaire Additional Questions – 2

DIRECTIONS: For each of the following statements mark the one best response. Notice that th response scale changes on each item.

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

1. Yes 2. No

What grade do you expect to receive in this course?

1. A +	5. B	9. C -	13. F
2. A	6. B-	10. D+	
3. A-	7. C+	11. D	
4. B+	8. C	12. D-	

In a usual week, how many hours did you spend outside of class studying statistics? Give only c

single numeric response that is a whole number (e.g., 3) _______________

	Very low					
In the past week, how would you describe your overall stress level?	1	2	3	4	5	6

Please check that you have answered every question in this section (unless you intentionally left the question blank).

THANKS FOR YOUR HELP!

Appendix C

Introduction to Statistics for the Social Sciences

Instruction for Read and Reflect on a Social Science Research Paper

Individual Reflection is Due (in paper format): Second Tutorial

Group Reflection is Due (in paper format):

Purpose:

The purpose of this task is to develop your statistical literacy. You will learn how to read, interpret and justify statistical information that are presented in a Social Sciences research article of your choice. Additionally, you will have the opportunity to collaborate with your peers, something you will encounter in your future professional life. I hope you value this task and enjoy your time discussing your selected article with your peers.

Task:

1. Your first individual task is to select a social science research paper that includes basic descriptive statistics, tables, and/or graphical displays. You may select your paper from:

- a journal article;
- any credible source, for example, Statistics Canada, or an organization (e.g., OECD);
- articles that you have already read for your previous social sciences courses or are currently reading in your social sciences courses.

   A list is provided on page 3 which will assist you in selecting your paper. I encourage you to spend some time exploring the suggested sources (it includes many topics that will interest you).

2. You will work in a group of three or four students from your tutorial who are in similar program as yours (in Social Sciences). You will individually propose your selected article to your group and agree on one of the articles as your read and reflect paper. As a group, you will read and reflect on your selected paper's data collection, representation, analysis, and interpretation. You will also reflect on any statistical methods that were chosen to address the study's research question(s) and propose other techniques that may be suitable for this type of study. For expanding the scope of this type of study, you will propose a future research question and a statistical method that you will learn in this course which can answer that research question.

A list of components that your reflection requires to address is provided on pages 4 and 5.

Individual Reflection – Due in your Second Tutorial:
For your second tutorial (week 3 of the course), you will, individually, select a social-sciences based research article (see the suggested sources on page 3 for selecting an article) and will address, in one page, the components 1 and 2 from the list of components to consider which are provided here on page 4. You will bring your individual reflections for components 1 and 2 to your second tutorial. In your tutorial, you will discuss, with your peers and your TA, your selected article's reflections for components 1 and 2.

Formation of Group Members:
In your third tutorial (week 4 of the course), a sheet will be circulated in class that will ask about your program of study. You will be grouped with your peers from similar program of studies. There will be three to four members in each group. You will know of your group number and their members in the following week, your forth tutorial (week 5 of the course). Each group will have a group blog, on portal, in which group members can start communications.

Final Presentation of Your Reflection:

*Two items are due on in the lecture:

- **Group Article's Reflection (along with a copy of your article*):**
  Each group will **submit one paper** in the lecture. Papers should be, no more than five pages (excluding the title page), no smaller than 12-point font size, e.g., Times New Roman, and double-spaced. Title page must include your group number, group members' first and last name, and your selected article's reference (proper referencing, e.g., MLA or APA format). ***Please attach a copy of your article with your paper.**

- **Self- and Peer-assessment**:
  Each member of a group will submit **in paper format** their self- and peer-assessment in the lecture*. Please use the document, **Self- and Peer-assessment** in the **Read and Reflect folder** on Portal for completing your assessments.
  *If you experience unseen circumstances which prevents you from submitting your assessments in-person, you may submit your self- and peer-assessment electronically to me, Asal:

***Course Incentive {Bonus Marks will be added to your final course grade}**

You are welcome to make a visual presentation (e.g., poster, pamphlet, concept map, or mind map) or vocal presentation (e.g., video, or voice over power point) of your Read and Reflect group project. You may refer to the "Read and Reflect" folder on portal for examples, previous works of former students in this course. You will receive bonus marks that will be added to your final course grade for a creative, clear, and organized visual or vocal presentation of your Read and Reflect project. If you wish to make a poster, please see me for large papers (refrain from making/ordering costly posters). Treat this poster making as a draft of future professional poster making. You will drop off your poster or any other visual forms of your work to Asal's office on the due date.

Selecting a Social Science Research Paper

1. Research Articles

- The Sage Encyclopedia of Social Research
- Social Sciences Abstract
- Sociological articles
- Worldwide Political Science Abstract
- PISA International

2. Statistics Canada: http://www.statcan.gc.ca/start-debut-eng.html

3. Ontario ministries: https://www.ontario.ca/page/ministries

4. City of Toronto:

http://www1.toronto.ca/wps/portal/contentonly?vgnextoid=1e68f40f9aae0410VgnVCM10000071d60f89RCRD

5. The Organisation for Economic Co-operation and Development:

http://www.oecd.org/

http://www.oecd-ilibrary.org/

6. World Statistics: http://world-statistics.org/

7. UNdata: http://data.un.org/

Components to Consider: Reflecting on Your Research Article

Part A. Informal Statistical Inference (Chapters 1 to 4)

1. Think about the study's background (the context of the study):
   a. Identify the purpose.
   b. Identify the research questions (hypothesis).
   c. Identify the variables in the research questions (hypothesis).
   d. Identify the types of variables (Quantitative [discrete, or Continuous] or Categorical [Nominal, or Ordinal]).
   e. If the study aimed at investigating relationships between variables, identify which variables in the study were treated as response variables and which ones were treated as explanatory variables.

2. Think about the study's data collection:
   a. Where did the data come from? (e.g., from which population)
   b. When was the data collected?
   c. What type of study was this? (e.g., observational, survey)
   d. Who were the cases in the study? (e.g., participants)
   e. What procedure(s) and instrument(s) were used for this study?

3. *Think about the graphical displays that were used in this study:
   a. If there is no graphical display, propose at least one graph that would be appropriate for describing the variables you identified in question 1.
   b. Describe any obvious patterns you observe in the graph(s).
   c. Does your interpretation in part b. match the author(s)'s view? Briefly explain.
   d. To what extent, do you think, the graph(s) hide or distort pattern? If they do, propose a solution that will enable one better to understand the trend in the data within the context of this study (e.g., a different graph/representation).

   **Please copy and paste the graph(s) of your article that you are discussing in your paper.*

4. **Think about the tables that were presented in this study:
   a. If there is no table, propose one or create at least one table based on the summary statistics (e.g., means, percentages) mentioned in the analysis. Explain the purpose for including your table in this study (e.g., how would this table be useful?).
   b. Describe any obvious patterns you observe in the table(s).
   e. Does your interpretation in part b. match the author(s)'s view? Briefly explain.
   c. To what extent, do you think, the table(s) hide or distort pattern? If they do, propose a solution that will enable one better to understand the trend in the data within the context of this study (e.g., a different representation).

   ***Please copy and paste the table(s) of your article that you are discussing in your paper.*

5. Think about the summary statistics in this study:
    a. Were there any unusual observations in the data? If so, how were these values treated in the analysis? e.g., what were the researchers' decision about including or excluding any potential extreme observations?
    b. What other, possible, summary statistics do you think would be necessary to include in the study's analysis for making sense of data?

Part B. Formal Statistical Inference (Chapters 5 to 9)

6. ***Think about any statistical methodologies used to address authors' research questions.
    a. What statistical methodologies were used?
    b. Are the claims made valid and supported by data? e.g., how did the researchers check the proposed statistical models for their adequacy?
    c. What other, possible, statistical methodologies are suitable for this type of study? (e.g., think of other statistical methodologies that can be used to answer the authors' research question(s)).

7. ***Think about the ways in which you can expand the scope of the study. Propose one future research question and a statistical methodology that can answer your proposed research question.

    ***Note that formal statistical methodologies are those we learned about in chapters 5, 6, 7, 8, and 9. Your task, here, is to identify which statistical methodologies, for example, confidence intervals, or significance tests, were used in your article, and perhaps what other statistical methodological approaches would be suitable for this type of study. In the case where your selected study has only reported descriptive statistics, that means no formal statistical methods were employed, you will only think about component 7.

Appendix D

Read and Reflect Success Criteria

A. Group Timeline and Reflection Submission:

In the upcoming weeks, plan to collaborate with your group members. Except for the due date, all other timelines are proposed time frames for keeping your group on track. You may wish to revise those times if some other agreed meeting times work best for your group. You may want to refer to some paper examples of former students of this course in the Read and Reflect folder on Portal. I encourage all of you in your group to partake into thinking about each of the components to consider for your group's reflection. In doing so, your submitted group work will sound cohesive and clear for the marker. Best wishes ☺

Timeline	Task
	Claim your group article (choose among the ones you have individually selected or find a new article if that works best for your group). Work on Components 1 & 2 from the list of Components to Consider (Read & Reflect Instruction).
	Work on Component 3 from the list of Components to Consider (Read & Reflect Instruction).
	Work on Component 4 from the list of Components to Consider (Read & Reflect Instruction).
	Work on Component 5 from the list of Components to Consider (Read & Reflect Instruction).
	Work on Components 6 & 7 from the list of Components to Consider (Read & Reflect Instruction).
Due Date	Two items are due: • **Group Article's Reflection (along with a copy of your article*):** Each group will **submit one paper** in the lecture. Papers should be, no more than five pages (excluding the title page), no smaller than 12-point font size, e.g., Times New Roman, and double-spaced. Title page must include your group number, group members' first and last name, and your selected article's reference (proper referencing, e.g., MLA or APA format). ***Please attach a copy of your article with your paper.** • **Self- and Peer-assessment**: Each member of a group will submit **in paper format** their self- and peer- assessment in the lecture*. Please use the document, **Self- and Peer-assessment** in the **Read and Reflect folder** on Portal for completing your assessments. *If there any unseen circumstances that prevents from submitting your assessment electronically, you may submit your self- and peer- assessment electronically to me, Asal:
Course Incentive: Bonus Marks	You are welcome to make a visual presentation (e.g., poster, pamphlet, concept map, or mind map) or vocal presentation (e.g., video, or voice over power point) of your Read and Reflect group project. You may refer to the "Read and Reflect" folder on portal for examples, previous works of former students in this course. You will receive bonus marks that will be added to your final course grade for a creative, clear, and organized visual or vocal presentation of your Read and Reflect project. If you wish to make a poster, please see me for large papers (refrain from making/ordering costly posters). Treat this poster making as a draft of future professional poster making. You will drop off your poster or any other visual forms of your work to Asal's office on the due date.

B. Each group member's responsibility:

- Read the chosen article agreed by all group members and individually prepare reflections based on the components to consider (read and reflect instruction sheet).
- Communicate individual reflections on each of the components to the whole group.
- Positively evaluate other group members' reflections on each of the components, and add or build on group members' reflections.
- Share strength in any area (e.g., editing the paper) that will make the group successful.

C. Overall Assessment (possible points: 30):

Overall assessment is based on group work, self-assessment and peer-assessment. Due to variation in peer-assessment, and perhaps in self-assessment, individual marks are expected to vary within each group. Although the aim of this project is to assign every member of a group the same mark, however, for fairness and due to unseen circumstances, individual marks may vary.

Assessment Criteria	Possible Points
1. Assessment of your group article's reflection	14
2. Self-assessment	8
3. Peer-assessment	8
Total	**30**

1. Assessment of group article's reflection (possible points: 14)

Title page (possible points: 2 points):
Your title page should include your group number, group members' first and last name, and your selected article's reference (proper referencing, e.g., MLA or APA format).

Seven components to consider from the read and reflect instruction (possible points: 12):
Clear and adequate reflections, based on the seven components to consider.
The detailed breakdown of possible points is as follow:
2 = "clearly and adequately addressed all parts of a read and reflect components to consider"
1 = "addressed some parts of a read and reflect component to consider"
0 = "missed addressing or inadequately reflecting a read and reflect component to consider"

Component	Possible Points
1	2
2	2
3	2
4	2
5	2
6* and 7*	2
Total	**12**

*Note that components 6 and 7 are combined into 2 points. Some articles report descriptive analysis. Therefore, in those articles, there are no formal statistical methods employed. In that case, the emphasis of your reflection should be placed on component 7 (future expansion of that type of study). Thus, it is best to combine these two components, 6 and 7, into one component.

2. Self- and Peer-assessment (possible points: 8 for each assessment)

Group Number: **First and Last Name:** **Student #:**

This part is strictly confidential. Think about the extent to which you and each of your group members contributed into this collaborative task, read and reflect. These include the assessment of the following four areas:

- **Accountable:** The extend to which a person demonstrated commitment to all group meetings.
- **Productiveness:** The extent to which a person completed the agreed divided task as set out by all group members by a specific timeline.
- **Supportiveness:** The extent to which a person supported all group members in order to ensure successful outcome.
- **Creativeness:** The extent to which a person contributed to overall clear representations of read and reflect final submission.

Each of the above area, measurement of interest, is an ordinal categorical response variable with the following levels: **"0 = Not at all", "1 = Somewhat", "2 = Adequate**"
Please assess yourself and each of your group member within each area, below, using the levels above. **Please sum the scores for each column.**

Area	Self-assessment	Member:	Member:	Member:
Accountable				
Productiveness				
Supportiveness				
Creativeness				
Total				

Note 1: If a member of a group is identified as "Not at all active" by all other group members for all specified areas above, then by fairness, this person's mark for this part of course evaluation will be 0% out of 10%. This person can speak to Asal for any objections/resolutions.

Note 2: Inactive group member(s) will not jeopardize all other group members' evaluations. However, if a group is left with only one active member, meaning all others are inactive, then this active member should notify Asal immediately (for resolution).

Appendix E

Letter of Consent

Dear student,

In the Summer term of 2016, the Department of Computer and Mathematical Sciences (CMS) is offering a new introductory statistics course, Introduction to Statistics for Social Sciences. This course is designed to meet the interests of students from Social Sciences. As a student in this course, you are asked to participate in a research study that investigates students' attitudes toward statistics.

The researchers for this study are your course instructor for STAB23, Asal Aslemand, and a statistics faculty member in the CMS department. Data collection will be managed by a course research assistant. The professor and the research assistant have no connection to your statistics course teaching and your evaluation of quizzes, course project, midterm, and the final exam.

Your participation in the course research study will involve the completion of a survey, Students Attitudes Toward Statistics, SATS-36© at the beginning of the course, and another time at the end of the course. Each survey will take about 10 to 15 minutes to complete. The surveys will be completed during the first and the last tutorials. The course instructor, Asal Aslemand, and your teaching assistants will not know that you have consented to participate nor if you have completed the pre- and/or post-course attitudes survey (SATS-36©).

By agreeing to participate you will allow the researchers to investigate the effect of this discipline-specific to teaching statistics course on your attitudes toward statistics, and its relationship to your course grades and all other course activities completed by you in this course. This means that the data to be analyzed will include, grades for your quizzes, course project, midterm, exam, and the course; additionally, the number of visitations that you will give to Math and Stats Learning Centre (MLSC) will be included into the data to be analyzed. Furthermore, your gender, program and year of study, grades that you obtained in any of your previous mathematics or statistics courses at the post-secondary level, current university GPA, and grades that you obtained in your senior level mathematics or statistics courses (e.g., the grades for your Mathematics of Data Management course in Ontario) at the high school level will be included in the data to be analyzed. This information will be obtained from your student record from the Office of Registrar.

Participation into this study is voluntarily. There is no penalty involved with participating or not participating into this study. If you agree to participate, you will receive 3-points participation mark added to your total quiz grade at the end of the course; that is after which the teaching assistants mark the final quiz, the quiz marks will be sent to the research assistant so that if you have participated into the study, the research assistant adds this 3-points to your total quiz marks. The research assistant will then calculate your final quiz average for the course and will send the final quiz average to the course instructor, Asal Aslemand, without identifying whether or not you have participated into this study. Thus, the course instructor, Asal Aslemand will be blind as to knowing that the 3-points are added to your quiz grades for your participation into this study.

By agreeing to participate, the research assistant will attach your consent form to the completed pre- and post-course survey (SATS-36©) and will assign a participant number to you. The course instructor, Asal Aslemand, and your teaching assistants will not know your participation number and will not know that you have consented to participate into the study nor if you have completed the pre- and/or post-course attitudes survey (SATS-36©). After the course is completed, the research assistant, will enter your responses to SATS-36© both at the beginning and at the end of the course into an excel file with your participation number (not your student number) for the data to be analyzed. The research assistant will add the information regarding your STAB23 grades for quizzes, course project, midterm, exam, and the grade for the course, and the number of visits that you gave to MLSC to that excel data file that has your participation number. The research assistant will also add the obtained information from your student record from the Office of Registrar regarding your gender, program and year of study, grades that you obtained in any of your previous mathematics or statistics courses at the post-secondary level, current university GPA, and grades that you obtained in your senior level mathematics or statistics courses (e.g., the grades for your Mathematics of Data Management course in Ontario) at the high school level into that excel file that has your participation number. The data file to be analyzed and for any future publication use is de-identifiable (e.g., the data file does not contain your student number).

You are free to withdraw from the study at any time. There is no penalty for withdrawing from this study. If you decide to withdraw, please contact the course research assistant. You will still be entitled to receive the 3-point participation mark added to your total quiz grade which will be managed by the research assistant in the same way that was explained in the fifth paragraph. In the case you withdraw, your data, responses to attitudes survey items (SATS-36©), information regarding your course grade (quizzes, course project, midterm, exam, and the grade for the course), and the number of visits that you gave to MLSC, and the obtained information from your student record from the Office of Registrar regarding your gender, program and year of study, grades that you obtained in any of your previous mathematics or statistics courses at the post-secondary level, current university GPA, and grades that you obtained in your senior level mathematics or statistics courses (e.g., the grades for your Mathematics of Data Management course in Ontario) at the high school level will be forever removed from this study's data set and thus will not be included into the data to be analyzed.

By participating into this study, you will, in general gain experience in a study. You will also contribute to the learning experience of the researchers, Asal Aslemand, the professor, and the course research assistant. You will contribute to improving the future teaching and learning of introductory statistics courses at the tertiary level and advancing the knowledge about the importance of studying students' attitudes toward statistics in Statistics Education.

Thank you for considering to participate into this study. If you have any questions about this research study, or if you wish to withdraw from this study at any time, you may contact the study research assistant (#Name of a CMS undergrad student).

First name: ______________________________________

Last name: ______________________________________

Student number: _________________________________

Signature: ______________________________________